INTEGRATION THEORIES AND SELF-RATING:
THE APPLICATION OF COGNITIVE ALGEBRA TO SCHEMA THEORY.

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Submitted in Partial Fulfilment

of the Requirements for the

Master of Psychology (M.Psych.)

Degree

at the University of Tasmania

(March, 1987)

to be conferred
1988

DECLARATION OF SOURCES.

The research presented in this thesis contains no material which has been accepted for the award of any other higher degree or diploma in any university and, to the best of my knowledge contains no material previously published or written by another person except where due reference is made in the text.

S. C

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ACKNOWLEDGEMENTS

I would like to thank all those who have assisted me in this project. My supervisors, Professor Don McNicol during the design and planning stages and Dr. Brian Mackenzie during analysis and drafting, provided invaluable time, enthusiasm and advice over what was, for all involved, a long and busy period.

I am also indebted to Rosalie Viney, whose boundless support, assistance and encouragement have made an arduous task bearable; to my fellow postgraduates for their friendship and advice, and to my subjects who gave their time and attention.

ABSTRACT

An experiment was conducted to investigate the appropriateness of Anderson's (1981) averaging integration model to self-rating. This model would enable simultaneous estimation of the extremity (or position) and importance (or weight) of those self-schemata involved in a given rating task (Markus, 1977). It was hypothesised that the averaging model of integration could be described geometrically as predictive of a "city-block" metric, such that estimates of proximity (self-descriptiveness of adjective-qualifier pairs) consist of summed estimates of the proximities of each component of the stimulus item to a constant comparitor point. Geometrically, this model therefore predicts that movement through the space in which rating takes place is horizontal and vertical, but never diagonal. This model is contrasted with a euclidean metric in which ratings are predicted from the square root of the summed squared proximities.

Stimulus items consisted of pairs of adjectives, each qualified by one of six adverbs.There were two Adjective Type conditions (Abstract, Concrete) and three Instructional Sets, yielding a 6 (qualifier of first adjective) X 6 (qualifier of second adjective) X 2 (adjective type) within-subject factorial design with Instructional Set as a between groups factor.

Data were visual-analog ratings from 0 (not at all like me)

to 100 (exactly like me). These were subject to a range of model fitting procedures intended to identify convergence with the averaging and euclidean models, including Median Polish (Tukey, 1975), IMSL iteration procedures, and residuals ANOVA (Anderson, 1982).

Results indicate that neither the averaging nor the euclidean models satifactorally predicted the ratings obtained, as the data departs significantly from each. Of the two models, however, the euclidean model shows superior fit to the data.

It is suggested that the results may be consistent with a differential-weight averaging model (Anderson, 1982), although evidence to his conclusion is secondary.

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CHAPTER ONE: SCHEMATA, SOCIAL SCHEMATA AND SELF-SCHEMATA

1.1 "SCHEMA" AS A PSYCHOLOGICAL CONSTRUCT

The word "schema" has had diverse and often unsatisfactory usage since it entered the psychological lexicon. Bartlett (1932), incorporating the word into his general theory of memory, expressed concern about the term as being "at once too definite and too sketchy". In spite of this reservation, Bartlett became one of the first researchers to apply the word "schema" to a product of memory.To Bartlett (1932), a schema is:

> ...an active organisation of past reactions or of past experiences which must always be presumed to be operating in any well adapted organic response.

; a "combined standard" of stored experiences and responses which shape and modify any current experiences and is itself continually adapting and adjusting with the passage of life events. "Schemata", to Bartlett (1932) are in many ways the cognitive parallel to Broadbent's (1958) perceptual filter - both constructs influence the perception, storage and retrieval of information, and both are defined only functionally. The comparability of these two constructs is illustrated in a study by Bargh (1982), in which dichotic listening- a favoured perceptual filtering task- is utilised in an investigation into the cognitive salience of a range of self-descriptive items.

Although Bartlett (1932) identified schemata strongly with functions of learning and memory, the concept lapsed from cognitive research until recently (e.g. Rogers, Kuiper and Kirker,1977), while a more vigorous social psychology literature has adopted and used the term to describe a range of related but conceptually quite distinct entities. DeSoto and Kuethe (1958) describe a set of principles as to the structure and operation of social relationships, which is subsequently (Kuethe, 1962, Kuethe and Weingartner 1963) ascribed the title "social schemata". Devices used to access these sets of principles include the matrix of predictions about the nature of a hypothetical interpersonal relationship given the truth of premise relationships (DeSoto and Kuethe, 1958) and the placement and recall of the location of various "social objects" (two dimensional pictures of men, women, children and neutral shapes) in space (Kuethe 1962, Kuethe and Weingartner, 1963), this latter task resting heavily on the assumption that the choice of spatial placement reveals in some meaningful way the subjects' perception of the relationship between the objects placed. Noteworthy in early conceptualisations of "schemata" such as this is a readiness to describe schemata completely in functional terms, such that the schema is that thing which brings about the observed response. Kuethe and Weingartner (1963), for instance note that:

> In these earlier studies, male college students employed a very popular schema, which placed a man figure together with a woman figure. other objects were not allowed to intervene...This powerful

> schema caused Ss to replace a man-woman display with the figures too close together.

;the SCHEMA, not the subjects, placed the figures together, or else, the "powerful schema CAUSED" the subjects' reponses. This casual functionalization of the definition of "schema" has rendered the discussion of "schemata" almost meaningless without reference to the task by which the "schemata" are being assessed. There may be no compelling conceptual reason to assume that the same forces determine prediction of a relationship as those that bias our placement of human forms in space, yet the ascription of the word "schema" to both these constructs lends spurious generality to the definition and methodology. This tendency to produce "schemata are what schemata do" definitions in the absence of consistent methodology has continued throughout research in this area and has resulted in a wide variety of definitions, each with slight task-specific differences in emphasis.

Zajonc (1968), reviewing this early schema literature describes this social psychological notion of the schema as comprising a set of social theories which are continually undergoing revision and rejection, a dynamic and unrelenting process of change and discovery which result in the formation of abstract and unconscious principles of human activity and relating. This view of schema both contrasts and complements more cognitively based definitions such as that of Bartlett (1932), in which there is a tendency to regard schemata as repositories of life experiences which influence the processing of information by processes akin to filtering or selective attention. To an extent this division, with the cognitivists favouring a rather more passive, storage-based notion of the schema which contrasts with the information-seeking and self-promoting schemata of the social psychologists, remains.

Piaget (1952,1971) casts a yet broader definitional net, identifying schemata with observed consistencies and abstracted principles of behaviour. He defines an "action schema", for instance, as:

> ...whatever there is in action that can thus be transposed, generalised or differentiated from one situation to another.
>
> (1971,p6.)

An "action schema" is thus a continuing principle of action, an assimilation of general action patterns which is subject to continuing revision and elaboration as action becomes more complex. A schema may be concrete or abstract, learned or instinctive, global or specific provided it represents a continuing generalisation of some aspect of human behaviour. This definition captures the literal meaning of "schema" as a plan or structure, but shares little with the cognitive and social psychological notion of the schema as a construct possessed by the individual. Piaget uses the term "schema" to describe behaviours, whereas it is used by others to explain the origin of behaviours.

1.2 "SELF SCHEMATA"; CONCEPTUAL DIFFICULTIES AND OPERATIONALISATION

Markus (1977) is critical of these early typifications of "schemata", dismissing them as:

> ...vaguely defined heuristics with no real empirical moorings... viewed primarily as epiphenomena, inferred on the basis of behaviour or invoked in various post-hoc explanations.
>
> (P.64)

and argues for a more stringent operationalisation of the concept. It is to this operationalised concept of the term "schemata" that we owe the term "self- schemata", defined by Markus (1977) as:

> ...cognitive generalisations about the self, derived from past experience, that organise and guide the processing of self related information contained in the individual's social experiences.
>
> (p.64)

However, despite Markus' (1977, Markus, Smith and Moreland 1985) continued insistence on strict operationalisation, problems associated with repeated functional redefiniton have continued through the predominantly social-cognitive self-schema research. Perhaps the most telling of these problems is that of enumeration- how many schemata can a person be expected to possess?

While Markus (1977) clearly intends that one has a schema for a given attribute- a schema for dependence, a schema for generosity, and so-on, and thus that one's personality is a collection of schemata, Kuiper and colleagues (Kuiper and Rogers, 1979, Rogers, Kuiper and Kirker, 1977), despite agreeing that one does have a schema for a single attribute, also argue that "the self" can be seen as "... a grand or superordinate schema" (Rogers, Kuiper and Kirker, 1977, p.697) - a meta-schema comprising both one's beliefs about onesself (the self-schemata) and one's beliefs about the relationships between, and relative importance of, those beliefs (the superordinate schema - the self). While conceptually plausible and experimentally justified, this terminology, which effectively states that several schemata are equal to one schema, probably complicates the quantification issue beyond necessity. Lord (1980), continues with the Rogers, Kuiper and Kirker (1977) terminology, with the added complication of using "schemas" as the plural and "schemata" as the singular. He regards the self-schema as a "cognitive framework" of propositions about the self, the framework, rather than the propositions themselves being the self-schema.

Further complication has been added by a recent tendency to define schema neither as propositions per se nor the framework in which the propositions are aligned, but to speak instead of people as having a schema for a personality type. Strube, Berry, Lott, Fogelman, Steinhart, Moergen and Davison (1986), for instance, investigate the differences between subjects with "Type A" and "Type B" self-schemata by examining differences in self-description, reaction time to descriptors, and recall of words related to "type A" and "type B" personalities. Besides revealing the extent to which schema theory and trait theory have come to parallel each other, this terminology adds another possibility to the quantification of schemata. Subjects in this study are not defined as having a cluster of schemata that combine in such a way as to produce "type A" characteristics, but simply as having "a type A schema"- a single self- description to the effect that one is of Type A. This enlarges upon even the Rogers, Kuiper and Kirker (1977) terminology, since it presupposes that schemata, like traits, come in natural types or clusters of some description. The difficulty that is arising is that it would now seem impossible to state what aspects of human behaviour are or are not the products of particular types of "self-schemata", not on the basis of empirical certainty, but on that of conceptual and terminological imprecision. Currently one could correctly call a single proposition about onesself a "schema" (after Markus, 1977), one's entire sense of personhood a "schema" (after Rogers Kuiper and Kirker, 1977) , and the general categorisation of what sort of person one is a "schema" (after Strube et. al. 1986).

The only feasible solution to such imprecision is to generate and adopt a single, meaningful operational definition of "schemata", one which retains certain key qualities from the foregoing literature, but which makes continuing experimental research possible and comparable. Markus (1977) has argued that her method of classification of "schematics" and "aschematics" for a given behavioural domain provides such a definition. However, as shall be discussed below, these methods of classification and distinction of subgroups is itself conceptually imprecise.

Markus (1977) regards self-schemata as a set of firmly held, presumably verbal propositions about the self, derived from the full range of social and non-social experience:

> Self schemata include cognitive representations derived from specific events and situations involving the individual... as well as more general representations derived from repeated categorization and subsequent evaluation of the person's behaviour by himself and by others around him. (e.g. "I am very talkative in groups of three or four, but shy in large gatherings, "I am generous", "I am creative", "I am independent".
>
> (p.64)

These "cognitive generalisations" are often typified by Markus as a list of self-descriptions in which the individual is placed at a single point along a stated bipolar dimension, with the degree of "schematicity" , indeed the existence of the schema at all on that dimension being determined by a combination of the extremity of this position and the importance of that dimension as a whole in the person's self-concept. It becomes possible, therefore, to allocate people to groups on the basis of the polarity and importance of their schemata in various domains, and this provides the basis for Markus' (1977) operational definition of "Schematics" and "Aschematics" for a given behavioural domain. Her criteria for membership of each group are first stated in her 1977 classification of Dependents, Independents, and Aschematics.

For the purposes of classification in the domain of Dependence-Independence, Markus (1977) asked subjects to rate themselves on various trait adjectives relevant to this dimension, to endorse items on the adjective checklist and to rate on an 11-point scale the importance of the rated traits in their attitudes about themselves. Three groups are defined on the basis of these tasks. "Independents" were:

> "those subjects who rated themselves at the extreme end (points 8-11 on an 11 point scale) on at least two of the following semantic differential scales: Independent-Dependent, Individualist-Conformist, or Leader-Follower, and who rated these dimensions as "important" (points 8-11 on an 11 point scale), and who checked themselves as "independent" on the Adjective Checklist".

"Dependents" were those who rated themselves at the other extreme (points 1-4) on at least two of the three dimensions described above, who ascribed 8-11 points of importance to these dimensions, and who endorsed "dependent" in the adjective checklist. Finally, a group of subjects termed "Aschematics" rated themselves in the middle (4-7) range on two of the three above dimensions, did not endorse either "dependent" nor "independent" in the checklist task, and "fell in the lower portion of the importance scale".

Specific criticisms can be lodged at aspects of these operational criteria, which Markus has preserved in form throughout her schema research. There is a ring of undue arbitrariness to the two out of three and 8 to 11 criteria. There is also a methodological fuzziness surrounding the importance ratings required in order for a subject to be deemed "aschematic", with no criteria stated beyond that those so categorised had scores which "fell in the lower portion" of the scale. Further, it becomes possible for a person to be categorised as highly schematic for, say "dependent", while having rated themselves as "independent " on the sematic differential scale, since the other criteria could be met without this rating. Arbitrariness is, however, in many ways a price of operationalisation, and the validity of such criteria are only to be borne out in their explanatory and experimental usefulness. A more important concern is with the categorization of the "aschematic" group, described by Markus as "without schema on this dimension" (p.66), since this group is clearly intended to contain only those who have no "cognitive generalisation about the self" in the domain of dependence and independence. This therefore is a category of conceptual as well as of definitional concern, as the success of the inclusion criteria hinges upon the confidence that those who ought to have been excluded have been. The role of the "importance criterion" in ascribing membership to this group is crucial to understanding the Markus (1977) conceptualisation of schemata.

1.3 THE ROLE OF DIMENSION IMPORTANCE IN DETERMINING SCHEMATICITY

Markus' (1977) "importance criterion"- that subjects will only be termed schematic for a domain if that domain is important to their self-concept- is included to accommodate the possibility that a subject could be highly schematic for a position midway along the bipolar scale. The imposition of the criterion implies that nobody who rates the dimension as highly important can be categorised as "aschematic". Conversely, however, the criterion makes manifest an assumption by Markus that schemata are necessarily important in one's self-evaluation. Markus, Smith and Moreland (1985) make a methodological improvement to the use of the importance criterion by specifying more precisely a criterial level of "unimportance" at which a subject will be deemed "aschematic". The domain being investigated in this study is masculinity, and the criterion tasks are parallel to those of Markus (1977)- semantic differential rating, adjective endorsement and importance ratings. The significant methodological difference between this and the earlier study is that an "unimportance criterion" is set for membership of the aschematic group- to be termed "aschematic" subjects had to rate two of the three dimensions related to masculinity between points 8 and 11 (11 in this case representing 11 "not at all important" and 1 " most important"). While it is more methodologically complete, this innovation serves to emphasise, rather than to resolve the problem of the importance criterion in determining a person "aschematic". If, as Markus (1977) claims, a schema is a learned generalisation about the self, and the "self-schema" is the set of such generalisations, then these generalisations could reasonably be expected to be distributed along the dimension of importance, with some schemata being very important indeed and some being almost completely unimportant- they are no less cognitive generalisations about the self by virtue of not being particularly prominent in self-evaluation. If a schema is defined as a learned self-description then importance, as well as extremity, is more sensibly seen as a <u>feature</u> of the schema under investigation, rather than as a <u>criterion</u> for determining whether the schema is present or absent.

Empirically, both extremity (or position) and importance (or weight) are central to a person's schema in a given domain. Markus, Smith and Moreland (1985) report that the correlations between these variables have ranged across studies between 0.78 and 0.89, indicating that this relationship is strong and positive. While this would be a predictable finding- that those who occupy more extreme positions on dimensions also value those dimensions more highly in their self-description- it is also an important one, and not one to be subsumed as a consequence of the definition of "schema". An adequate understanding of schemata therefore demands simultaneous estimation both of where a person is placed on a descriptive dimension and of how prominantly that dimension features in self-description, as well investigation into the extent of covariance between these two variables. It shall be argued that the adding and averaging models described by Anderson (1965, 1981, 1983) provide potentially useful algebraic and geometric descriptions of subjects' performances on self-rating tasks. The present study investigates the applicability of Anderson's averaging model and an alternative Euclidean model to the assessment of position and weight of rated dimensions in a simple rating task.

CHAPTER TWO: SELF-SCHEMATA, FUNCTIONAL ALGEBRA AND COGNITIVE GEOMETRY

2.1 SELF-SCHEMATA AS PERSONALITY DIMENSIONS

Nelson and Hayes (1981) usefully describe personality as " a cluster of points in N-dimensional space", a description that is applicable to both trait and schema typifications of "personality" . That part of the individual that is consistent across time and space can be viewed, at least by analogy, as a network of habitual or otherwise enduring positions on a series of behavioural, attitudinal or self-descriptive dimensions. The "uniqueness" of the individual, on this interpretation, is a manifestation of the uniqueness of the complement of the set of dimensions, the cluster of points so defined, and the relative prominence of various dimensions in the individual's behaviour or self-description.

This understanding of "personality" is applicable to the interpretation of schema theory, and while by no means capturing the subtlety of the theory, particularly as regards the information processing roles of self-schemata, it enables certain implications of schema research to be investigated using geometric and algebraic models of information processing. From Markus (1977), for instance, it can be understood that a person having a schema for "dependence-independence" can be described as i. Having within her cognitions about herself a conceptual dimension reaching from the most dependent possible person to the most independent possible person, ii. Habitually occupying or endorsing a position some specifiable distance along this dimension, and iii ascribing a quantifiable level of importance to this dimension in her description of herself. This view -that self-schemata can sensibly be seen as a set of propositions endorsing points upon a range of conceptual dimensions- has lead many writers to describe schemata in terms parallel to those used in descriptions of traits, the key difference being that schemata are always products of learning and thus subject to change. Rogers, Kuiper and Kirker (1977) draw this parallel:

> More than likely a portion of the list... [of terms describing "the self"] ... consist of general terms- not unlike traits- that represent the abstracted essentials of an individual's view of self
> (p.677-8)

2.2 THE GEOMETRY OF INTEGRATION

If schemata can indeed be conceptualised as points upon variously weighted conceptual dimensions, then their product- the behaviours or attitudes held by the individual- represent some form of nett output of this cluster of points, with the nature, polarity and importance of the output corresponding in some way to the existence, extremity and weighting of the dimensions relevant to the task. For a self-rating task, then , a person's response to a single stimulus item demanding combination of more than one dimension may be taken as a manifestation of the relative extremity and weighting of those schemata called upon. If this were the case, it ought be possible to identify the procedure by which the schemata are combined by modelling produced response in terms of mathematical or geometric principles. The simplest possible such model would state that the output is a weighted sum of the positions of the schemata called upon, an instance of Anderson's (1965, 1981, 1983) general principle of additive or averaging information integration.

This adding or averaging model can be depicted geometrically as a "city-block" metric, that is, it predicts that subjects "move" from the object being rated to some hypothetical fixed comparitor point horizontally and vertically along the dimensions involved in the rating, with the distances so moved being added to produce the observed response. Consider, for instance Anderson's (1981) meal rating task,in which subjects are asked to rate how much they imagine they would like certain given combinations of vegetable and main course. The stimuli to be integrated are main courses and vegetables, and the single output an overall rating of likeability. Presumably an early stage of processing involved in performing this task is ascribing a likeability value to each stimulus given. Anderson (1981) refers to this process as the operation of the "Valuation function" (p5). Valuation involves the ascription of a value to the component stimuli (how likeable are sausages as a main course) and of a weight to the stimulus dimension as a whole (how much does the choice of main course influence my enjoyment of any meal?). Once Valuation has taken place, the "Integration function" combines the stimuli and gives rise to a "Response Function" which produces the measurable output.

For Valuation to occur in accord with the predictions of additivity, the scale value of all stimuli along a single dimension (the likeability of each main course) must be indexed conceptually to a single point. That is to say, additivity could not be observed if subjects were using entirely different notions of "likeability" for sausages from that which they are using for roast lamb. It must be assumed that in a single stimulus domain, subjects are making all ratings relative to some enduring standard. This stage of valuation- the ascription of scale values to stimuli can be conceptualised as the linear distance between the given stimulus and the standard, with the rated scale value of the given equalling its distance from (or proximity to) the standard. Thus the valuation function by which the given stimuli are provided with values along the response dimension can be described as depicted in Equation 1 :

$$S_{Ai} = |G_{Ai} - C_A|$$

[EQUATION 1]

,where S_{Ai} is the scale value of the i^{th} level of stimulus factor A.

C_A is the standard, or comparitor point on dimension A

and G_{Ai} is the given stimulus item.

The second process of Valuation, the weighting of the stimulus dimension as a whole, influences the magnitude of the effect of each stimulus in the overall integration, and can thus be described as a multiplying function. Geometrically, this multiplication serves to alter the absolute size of the stimulus dimension without effecting the relative placement of either the scale values or the comparitor point along it. An assumption made for the purposes of early analysis is that the weighting of a stimulus dimension is constant along the length of that dimension, and that therefore the weight of each dimension is a multiplicative constant, stretching or shortening the stimulus dimension by an amount that is constant along the length of the dimension.

The Valuation function for a simple two-dimension paradigm can thus be depicted graphically, with a point (G_{Ai}, G_{Bj}) representing the given stimuli on dimensions A and B, and the point (C_A, C_B) as the location of the comparitor points on dimensions A and B respectively:

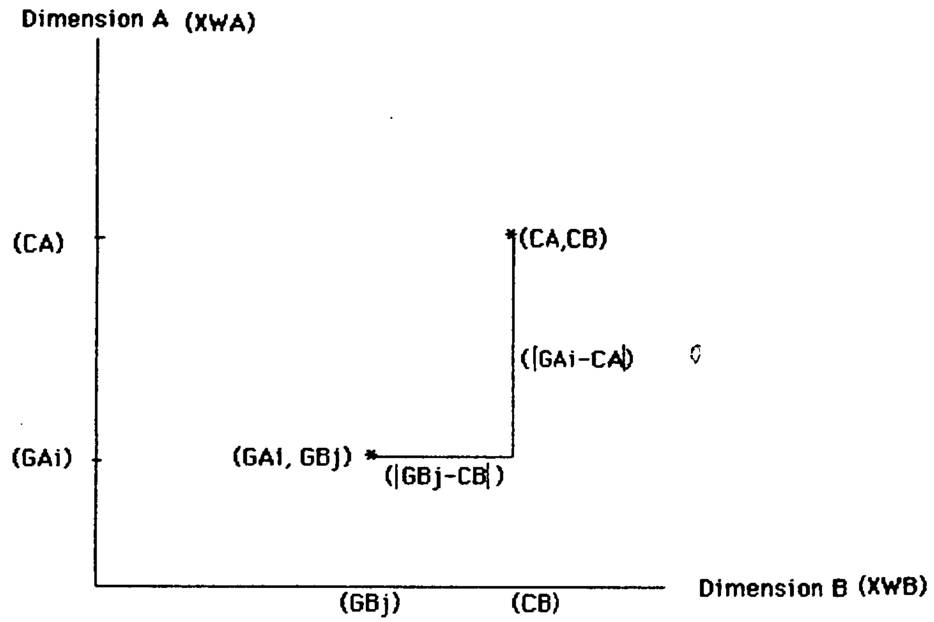


FIGURE 2.1 REPRESENTATION OF THE GIVEN STIMULUS VALUES AND COMPARITOR VALUES FOR DIMENSIONS A AND B AS POINTS IN TWO-DIMENSIONAL SPACE.

The Integration function of an adding-type model assumes that the response is a weighted sum of the scale values, thus that

$$r_{ij} = W_{Ai} \quad (|G_{Ai} \quad - \quad C_A|) \ + \ W_{Bj} \ (|G_{Bj} \ - \ C_B|)$$

[Equation 2].

,where r_{ij} is the response to the stimulus comprising the i^{th} level of factor A and the j^{th} level of factor B,

W_{Ai} is the weight of stimulus dimension A at level i,

and W_{Bj} is the weight of dimension B at level j.

An additive integration and valuation model thus predicts that a subject's rated response to a two-dimension complex stimulus in which weighting is assumed constant is equal to the sum of the distances along the horizontal and vertical axes between the given value on dimension A and a standard comparison point on that dimension, and the given value on dimension B and a comparitor on that dimension, with each distance multiplied by the weight of the respective dimensions. It is thus appropriate to describe this straightforward additive model as predictive of a "city block" metric, in which "travel" from one point in space to another occurs horizontally and vertically but never diagonally. A subject's response is the weighted sum of the distances thus travelled.

Simple additive models of information integration have been suggested for some time. Guilford (1931) investigated the extent to which subjects' reports of the pleasantness of colours corresponded to a weighted sum of the pleasantness of the component colours, and found that, while the additive model was explanatory, the integration process seemed more to parallel a process of stimulus averaging. Spence and Guilford (1932) similarly found that the rated pleasantness of odors is a weighted mean of the more pleasant and the less pleasant odor. The weighting of the two odors seemed determined largely by the extent to which one odor prevailed over the other:

> When one odor of the pair is dominant, it carries

> much more weight in determining the affective value of the combination than does the recessive odor. The affective weight of the dominant odor probably depends upon the degree of dominance.
>
> (p501)

Both Guilford (1931) and Spence and Guilford (1932) were unsuccessful in attempting to predict pleasantness ratings of the compound from a simple sum of the components, both found it necessary to regard the mechanism of integration as an average or weighted mean of the pleasantness of the components. Anderson (1981) has also found that a weighted averaging model proves more successful in any direct testing between the two:

> Adding and other linear models have been widely considered in psychology and have dominated research in some areas of decision theory and other fields. The intuitive plausibility and mathematical simplicity of these models have been major reasons of their popularity. When appropriate experimental tests have been made, however, the linear models have seldom succeeded. Simple critical tests have regularly ruled out linear models in many of the areas in which they have been most popular.
>
> Many of these tests have also supported the operation of an alternative averaging model.
>
> (1981, p59)

Forms of the averaging type integration model have been demonstrably effective in predicting responses for a large range of integration tasks. Beginning with Anderson (1962), who first observed averaging-type principles at work in person judgement, a large and diverse research system has developed around integration theory. Additive and averaging rules have been found to be explanatory of an enormous range of human judgements, including psychophysical estimation (Anderson, 1970), quantity judgements (Anderson and Cuneo, 1978), moral culpability (Leon, 1980, cited in Anderson, 1981), judgements of complex social stimuli (e.g. Manis, Gleason and Dawes, 1986), even judgements of preference for hypothetical contraceptive methods (Jaccard and Becker, 1985). Further studies (e.g Birnbaum, 1974) have found that even when additivity is apparently not present in raw rating data, what departures there are can frequently be attributed to nonlinearity of the rating scale used, and an adding or averaging-type model can be reclaimed through monotonic rescaling of the response medium. There is thus strong evidence to indicate that averaging type models, and occasionally multiplicative models, represent general principles of judgement formation, generalisable across all domains of judgement formulation. The application of this type of model to the rating of self-descriptive propositions, and investigation of its wider implications for schema theory therefore warrants experimental attention.

There are few substantial differences between an averaging and an adding model of information integration. Both predict parallelism (Anderson, 1981), that is, both models predict that a factorial plot of obtained data will consist of parallel lines. Indeed, both make the same predictions about the observable data from most rating experimentation. The essential difference between the models is that the averaging model divides the overall weighted sum by a constant representing the summed weights of the values. This reduces the absolute magnitude of the response range while preserving both the relative values of points along the dimensions and the weight of each dimension. The averaging model retains the multiplication of weight by value and the addition of products, as represented in Equation 2, with the sum then divided by the summed weights of the stimuli. Anderson (1981) includes the Initial State, S_o, in his mathematical representation of this model. S_o represents the prior beliefs or dispositions of the individual before entering the experimental situation, and can be likened to a representation of the origin of the scale, that is, the a priori tendency of the individual to respond at a certain position on any linear scale. Mathematically, then, the averaging model an be written as:

$$r_{ij}=(W_o\ S_o\ +\ W_{Ai}(\left|G_{Ai}\ -\ C_A\right|)\ +\ w_{Bj}(\left|G_{Bj}\ -\ C_B\right|)/(W_o+W_{Ai}+W_{Bj})$$

[equation 3]

,where W_o is the weight of the Initial state,

S_o is the scale value of the Initial State,

W_{Ai}, G_{Ai} and C_A are the weight, the given value and the comparitor value for stimulus dimension A, and

W_{Bj}, G_{Bj} and C_B are the weight, the given value and the comparitor values for stimulus dimension B.

For present purposes, this general form of the averaging equation can be simplified. In the experiment to be described, subjects are asked to rate on a visual-analog scale how true they believe certain two-component propositions are of them. Each proposition consists of two adjectives each qualified by one of five qualifiers (minimally, slightly, rather, reasonably, extremely) or left unqualified ,with the adjective-qualifier pairs combined by the word "and". The propositions to be rated are therefore of the form "Rather Dependent and "Extremely Calm", with the ratings ranging from "not at all like me" to "exactly like me". Pilot and other research (Cliff, 1959, Anderson and Lopes, 1974) has indicated that qualifiers function as multipliers, their combination with adjectives producing the "linear fan pattern" (Anderson, 1981) typical of multiplicative constants (See Appendix 1). A qualifier combined with an adjective, therefore, produces a single cognitive unit which can range from zero to infinity for that dimension. For "calm", for instance, the application of a qualifier to "calm" multiplies the unqualified word by a constant amount, producing a single compound that is located somwhere between "zero calm" and "infinity calm". Whether the "zero calm" point represents to the subject a notion of high anxiety,that is, the dimension is seen as bipolar, or merely a notion of "not calm", that is, the dimension is unipolar, is immaterial for the purposes of the present study, as the geometry involved , including the concept of the rating as an estimate of proximity of two points would not be affected by this cognitive, within subject variable.

The use of a range of qualifiers could therefore be expected to create a series of points along the single dimension described by the adjective, as a pilot study has demonstrated. As stated earlier, in preliminary model fitting the integration rule is to be regarded as one of equal weighting, in that it shall be assumed that the predominance of the two dimensions in self-description remains constant across all levels of each dimension. In this equal weight case, the weight of each instance of a stimulus dimension is equal to the weight of every other instance; W_{Ai} therefore equalling W_A and W_{Bj} equalling W_B, with W_o remaining a constant. As Anderson (1981) explains, the denominator of Equation 2 therefore itself becomes a constant for every pair of stimuli and the response a linear function of the two weights and scale values. The averaging model in this case closely resembles the weighted adding model described in Equation 2. Since the constant denominator effects only the absolute, not the relative magnitude of the ratings produced in a task where all responses are assumed to range between 0 and 1, it can be safely regarded as algebraically irrelevant.

The final simplifying assumption concerns the relativity of weights of the stimuli. It is assumed for present purposes that W_A and W_B sum to 1. This assumption can be made if one understands the response as being completely determined by the stimulus items, and thus the weighting being completely distributed between the stimuli. This assumption overlooks W_o, the weighting of the initial state or origin. However, as stated previously, the scaling of the response scale in the present task distributes all responses between 0 and 1, and therefore the constant effects of S_o and W_o can be assumed equal to zero. The assumption of relative weighting is described by Anderson (1981):

> However, the relative weight of any stimulus depends on the other stimuli in the set. In each set, the denominator term forces the relative weights to sum to 1, the condition for an average.
>
> (p64)

The averaging equation to be used initially in the present experiment, in the light of these two assumptions, can thus be written as follows:

$$r_{ij} = W_A \quad (|G_{Ai} - C_A|) + ((1 - W_A)(|G_{Bj} - C_B|))$$

[equation 4] .

where W_A and W_B are the constant weights of factors A and B respectively across all stimulus levels, and all other terms are as previously defined

This model is very similar to that depicted in Equation 2, the only important difference being that this averaging model constrains W_A and W_B to sum to 1. The mathematical rationale for this has already been discussed. Geometrically, however, this constraint implies that the greatest possible valuation of a stimulus unit is equal to the length of the dimension multiplied by 1.0, and thus the largest possible response is equal to the dimension length, a situation which will only occur when the weight of the other dimension in the compound it is equal to 0. As responses in the present task themselves range between 0 and

1, the averaging model will not permit a rated response that is greater than the unit. If weight is regarded as an index of dimension magnitude, the longest a dimension can be is one unit, and then only if the other dimension has no length.

The geometric prediction of the averaging model to be used in the present task can therefore be represented as follows:

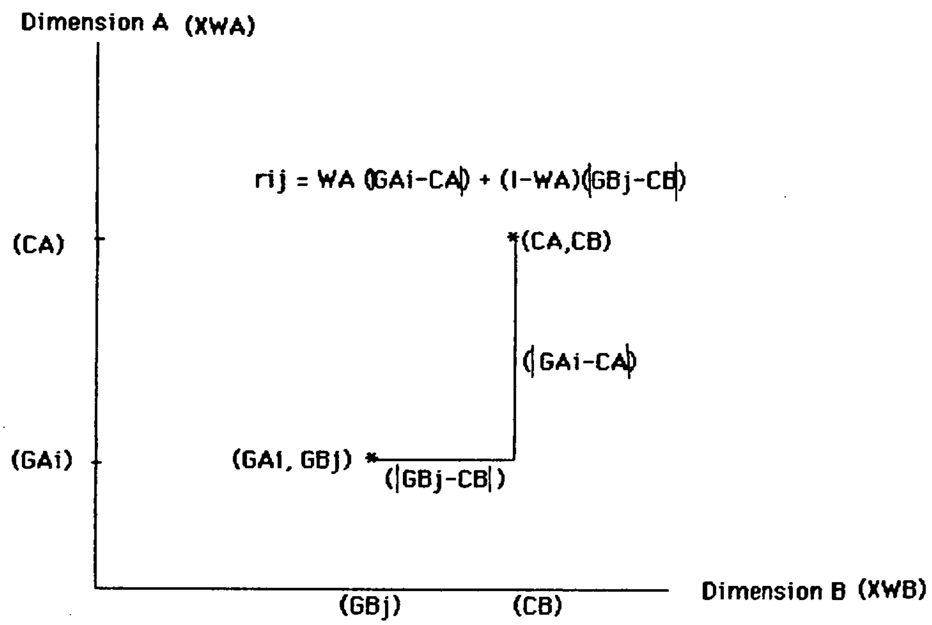


FIGURE 2.2: GEOMETRIC REPRESENTATION OF THE AVERAGING INTEGRATION MODEL .

The "comparitor" in this case is the point at which the subject would freely place herself upon this dimension, the "given", in this example, represents the point "Rather Dependent and Extremely Calm. The subject's placement and order of the qualifiers , the comparitor point on each dimension, and the weight value of the first dimension, would all, of course, be within subject variables, and would, if the model is found to fit the data obtained, be estimable by simple calculation from all proximity estimates for all given points. As with the additive model, the averaging model predicts "parallelism" (Anderson, 1965), in that it predicts that the change produced in moving from one stimulus level to another on one stimulus dimension (for example from "rather dependent" to "reasonably dependent") produces a constant additive change across all levels of the other stimulus dimension.

2.3 THE AVERAGING MODEL AND THE EUCLIDEAN MODEL

The major geometrically derived alternative to the city-block metric of the averaging model is a model which predicts that the proximity measures produced are not the sum of the distances along the horizontal and vertical axes, but the hypotenuse of the triangle so described. This Euclidean metric would predict that any rating produced is the square root of the summed weighted squares of the percieved proximity of the given and the comparitor stimuli, or, algebraically:

$$r_{ij} = \sqrt{W_A \ (G_{Ai} - C_A)^2 + \ ((1 - W_A) \ (G_{Bj} - C_B))^2}$$

[Equation 5]

,where all terms are as defined for earlier equations.

For the present task, therefore, the Euclidean metric can be depicted geometrically as follows:

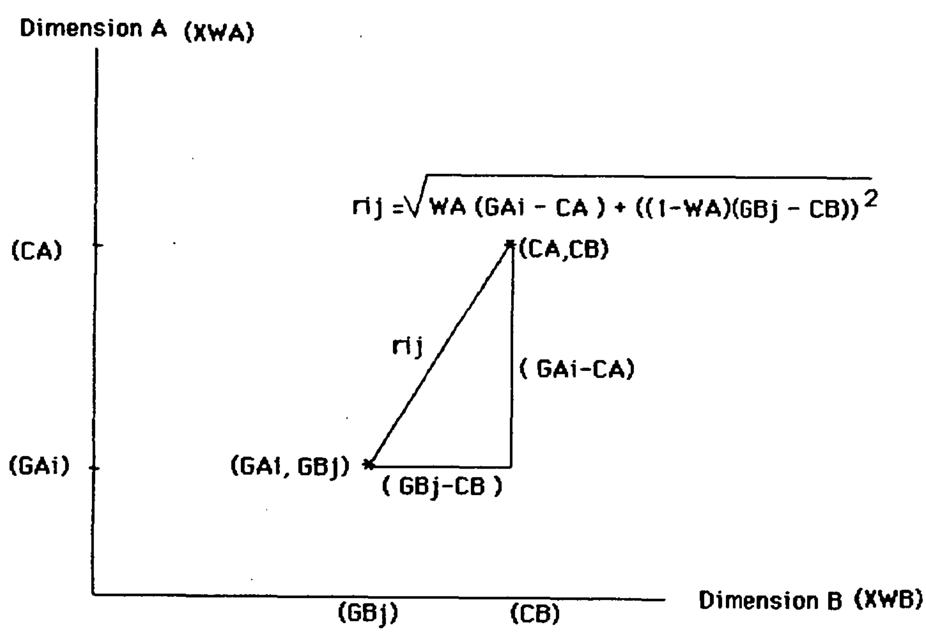


FIGURE 2.3: GEOMETRIC REPRESENTATION OF THE EUCLIDEAN INTEGRATION MODEL.

This model makes the assumptions of consistent and relative weighting as does the averaging model. However, the application of a Euclidean metric to this task makes the added assumption that the dimensions in question can be placed at right angles. This is not to say that "dependent" and "calm", and "tall" and "fair" (which are also stimulus items) are orthogonal, only that there is sufficient reason to assume, at least primarily, that they are treated independently by the subjects, that is, that every subject understands the two terms as having separate meanings, and will not actually confuse the meanings to the extent that a response is confounded by semantic uncertainty. Provided the subjects percieve the adjectives as semantically different, there is justification in regarding the task as operating in two dimensions. Given that the task is thus located in two dimensional space, this space can be depicted with perpendicular axes.

The Euclidean and averaging models, while involving essentially similar algebra, make quite different predictions about performance of subjects in a self-rating task. Both predict parallelism to the degree that both predict that the factorial plot of data obtained will contain no intersecting lines, however, the Euclidean model predicts some "bunching" of lines in the plot toward the more extreme ends, where the Averaging model predicts true parallelism. This is due to the nature of Pythagorean geometry - as a triangle tends toward equilaterality, the hypotenuse becomes relatively shorter for the same summed length of the remaining sides. Psychologically, this amounts to predicting a "VARIMIN" function within the integration procedure-subjects will rate as more self-descriptive items in which both components are moderately descriptive than those in which one is highly and one only slightly descriptive, summed side lengths and weights being equal. The averaging function, estimating only summed side lengths, makes no such prediction.

The differences in predicted factorial plot for the averaging and Euclidean models can be seen in Table 3, representing the predicted responses under the two models with all parameters held constant. The weights of the dimensions "dependent" and "calm" are 0.7 and 0.3 respectively, the scale values of the qualifiers are as follows: Minimally; 0.1, Slightly; 0.3, Reasonably, 0.4; Rather, 0.7; Unqualified, 0.8 and Extremely, 1.0. The comparitor position is described as; Dependent, 0.6, Calm, 0.4. With these parameters fixed, the factorial plots of the two models are depicted in Figures 2.4 and 2.5:

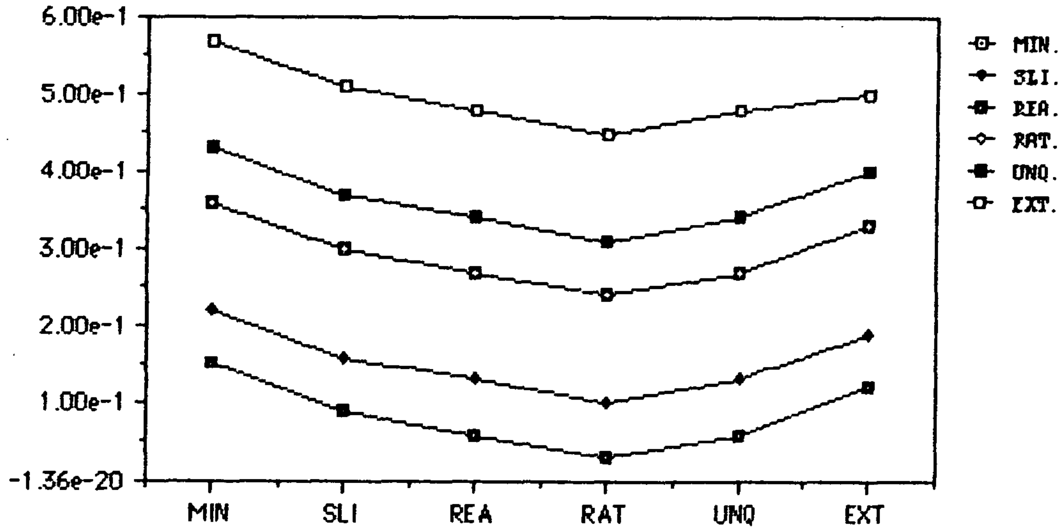


Figure 2.4 Predicted Factorial Plot of Data under the Averaging Model Parameters Fixed as Described in the Text

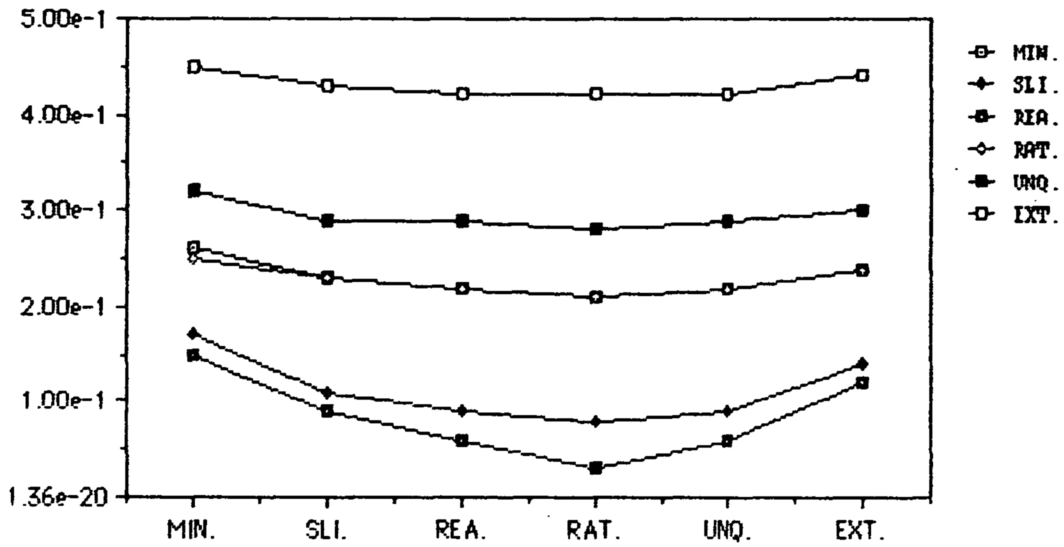


Figure 2.5 Predicted Factorial Plot of Data under the euclidean Model Parameters Fixed as Described in the Text.

If there is any plausibility in the conceptualisation of self-rating as task producing estimates of proximities of points in N-Dimensional space, it would be expected that either the averaging/city block or the Euclidean model should provide a reasonable fit to the data produced in this task, and this fit should provide a convenient measure of qualifier value, weight, and position of the stimuli involved. If, however, neither of these two simple geometric models provides an adequate fit to the data, then it will become necessary to investigate more complex arithmetic models, particularly those in which weight is not consistent across the length of the dimension. Among these are the extremity weighting model of Anderson (1981), various other differential weight averaging models (e.g Jaccard and Becker, 1985), and the Congruity model of Osgood and Tannenbaum (1955).

2.4 STIMULUS TYPES AND INSTRUCTIONAL SETS

Prior to discussion of the experimental procedure itself, two remaining points of methodology warrant comment. The procedures to be described in the present study, if found to produce data which successfully fit a simple geometric model, may enable a more detailed and convenient device for the understanding of the relative roles of weight and position in the processing of self-relevant information. However, is necessary to ensure that any results obtained can be presumed largely free of any systematic procedural artifact. Two types of such artefact are investigated in the present study - stimulus biasing and instructional biasing, and these shall be discussed briefly in the following section.

1. Stimulus biasing. Adding and Averaging integration rules have been applied to almost all domains of human judgement with unusually consistent success. However, it remains true that in general the most compelling demonstrations of the sucess of these models has been in their application to two domains: the estimation of physical attributes of observable, concrete stimuli, such as judged heaviness in a size-weight task (1981) or area estimations among children (Anderson and Cuneo, 1978), and in person likeability judgements (Anderson 1981, 1965). The application of the integration rules to more complex, abstract

information often requires some rescaling of responses or a somewhat more sophisticated averaging model than that for simpler judgements. It would seem that judgements of some types of stimuli are more patently additive than judgements of others, raising the possibility that the extent and existence of additivity in Anderson's results may be due to fortuitous selection of target stimuli rather than to true generality of the integration rules. In the present task, therefore, subjects are asked to rate propositions from two domains- they are asked to rate statements in which the adjectives "Dependent" and "Calm" are used, randomly intermingled with items in which the adjectives "Tall" and "Fair" are used. This simple inclusion of an adjective variable will enable analysis of the goodness of fit of the various models for both abstract and concrete target items. As all stimulus items shall be subjected to the same analysis, this manipulation will enable direct comparison of the integration rules applying to the rating of abstract and concrete self-referential propositions.

2. Instructional Biasing. The instructional set is well documented in cognitive psychology as a test of the robustness of cognitive phenomena to trivial change in the task description. Such manipulation of instructions is particularly important as regards integration theory for two key reasons. Firstly, there is intuitive appeal to the argument that how an experimenter describes an integration task may significantly influence the

type of integration process ultimately used by the subject. Secondly, the nature of the task- forming a single judgement from a complex stimulus item -is such that subjects could concievably go about it in several quite different ways. This applies particularly with regard to the rating of self descriptiveness, for which a full range of response tendencies has already been observed through various psychological literatures. Later "Barnum Statement " research, for instance, has suggested a tendency for subjects to endorse as self-descriptive not only the trivial, vague and positive descripitions typical of this research area, but also specific and often critical bogus personality feedback (e.g. Bradley and Bradley, 1977). Conversely, Schema theory workers (e.g. Markus, 1977) have reported that subjects who are highly schematic on a given domain are highly disposed to reject as entirely nondescriptive stimulus items which are only slightly disparate to their own position. In spite of the very different nature of these and Andersons' tasks, it is clear that both a tendency to endorse all statements and one to reject all but the exactly accurate would represent departures from predictions under additivity. The possibility must therefore be raised that the nature of the task and the manner in which it is described may substantially influence the rules by which judgements are made.

Gollob and Lugg (1973) investigated the extent to which additivity is a byproduct of the experimental task, both in nature and instructions. They exactly replicated Anderson's (1965) person perception experiment under various conditions of slight changes in stimulus format (embedding the target adjectives in a sentence rather than simply presenting two adjectives), and small instructional changes (omitting Anderson's instruction that equal attention be paid to the adjectives), finding that the additive effect found in the original study is robust over these changes.

No attempt, however, has been made to examine the robustness of adding-type models to instructional conditions which may be seen to actively bias subjects against an adding or averaging integration principle. In the present experiment, three different sets of instructions are used, with one third of the subjects being given each set. The instructions are identical in all but the paragraph describing the process of forming a judgement. The first set, described as "global", instructs the subjects to read the sentence carefully and rate how descriptive they percieve the sentence as a whole to be of themselves. The second instructional set, the "atomic" set, instructs them to read each part of the sentence carefully and make a single rating representing how descriptive each part is of them. It it intended that formulating the task description in this way will draw subjects' attention to the stimulus as a composite. The final set, intended to dispose the subject toward rejection of the stimulus, and therefore termed the "atomic negative" instructional condition, instructs them to read each part carefully and to accept the sentence as a whole as true only if they believe both parts to be true. This is the only instructional formulation which actually places conditions upon a subject's use of a particular point on the rating scale. By stating that subjects can endorse a sentence as true _only_ if both parts are percieved true, it is believed that this instruction will dispose subjects toward the "not at all like me" end of the scale, and may thus produce a departure from additivity at the upper ratings. That portion of the instruction containing the set manipulation is read once by the subject during the initial administration of the instructions and repeated by the experimenter once prior to the practice trials and once prior to the experimental trial. In all other respects, the instructions administered in the present experiment follow the guidelines described by Anderson (1981). The instructions used are reported verbatim in the Methods chapter of this thesis (Chapter Two).

This experiment thus contains checks on the robustness of the results obtained to minor and theoretically trivial variations in both the qualities being rated and the manner in which the rating task itself is presented to the subject, with adjective type manipulated within subject and instructional set across subjects.

2.5 SUMMARY OF EXPERIMENTAL INTENT

The experiment to be described herein investigates the extent to which the rating of self-descriptiveness of propositions can be seen to conform to certain stated algebraic, geometrically derived rules. The rating of the descriptiveness of propositions such as those used in this experiment is conceptualised as requiring the subject to produce a rating of the proximity between her own position on each given dimension and the the position indicated by the stimulus item. This proximity estimation is initially conceptualised as occurring within two-dimensional space, with the each axis representing one adjective , or the schema in the domain described by the adjective, divided into subjective units at the points described by the six qualifiers. The magnitude of each axis is determined by the weight ascribed to that domain by the subject. Successful fitting of the averaging or the Euclidean model would enable simultaneous estimation of the relative weights of the adjectives in the self-description, the subjective scale values of the qualifiers, and the standard point against which all stimuli are compared - the actual endorsed position of the subject for each domain described by the stimli. This would have implications for our understanding of the role of, and the relationship between, importance and extremity in self-schemata.

If neither of these simplistic models is found to provide an adequate fit to the data obtained, the experimental investigation will become one of model fitting, with systematic violation of assumptions made in the simpler models until, experimental power permitting, a more explanatory model is found. The implications of any departure from the initial models shall be discussed in the light of the required modifications.

CHAPTER THREE: EXPERIMENTAL METHOD

3.1 SUBJECTS

Subjects used in the present experiment were 19 adult females and 8 adult males (aged 18 to 45 years) selected through personal request by the experimenter. All subjects had English as a first language, and all were educated beyond matriculation, reducing the possibility of English literacy confounding performance in the task. Subjects were assigned in rotation to one of the three instructional set groups, the first subject recieving the "global" instructions, the second the "atomic negative", the third "atomic", and so-on, resulting in nine subjects in each of the three groups. The comparatively low numbers in each group is attributable to Instructional Set being the only variable that is not wholly assessable within subjects, and an observation on the basis of early analysis that any main effect for this variable was either nonexistent or extremely weak, neither of which was viewed as justification for continuing data collection. All subjects had normal or corrected vision and none reported any difficulty in reading or comprehending the stimulus items.

3.2 APPARATUS AND MATERIALS

Stimuli were presented on a General Corporation GC121 black and white television monitor controlled by a Unitron Microprocessor with Apple Pascal capability, which also recorded responses. Responses were registered on a 255 channel touch sensitive keyboard labelled at the left hand with the words "Not At All Like Me" and at the right hand end with the words "Exactly Like Me". Ratings made on this keyboard were converted by the experimental programme to values between 0 and 100, with 100 corresponding to the "exactly like me" rating. Subsequently these ratings were further reduced to between 0 and 1. Experimentation took place in a quiet, dimly lit laboratory free of distractions. Subjects were seated approximately 1m. from the screen and the stimulus items presented in 40 col. capital letters approximately 6mm in height. Written, laminated instructions were provided to the subjects to maintain consistency of administration.

3.3 STIMULUS SELECTION

The selection of the stimulus adjectives for the present study was based only upon the criterion that the items used must be of reasonably high frequency and each member of a pair be commonly recognised as of different meaning. It was also required, as discussed previously, that two of the adjectives be descriptive of objective, observable qualities, while the others were to be more subjective personal attributes. It was decided that the adjectives "Tall" and "Fair" and "Dependent" and "Calm" satisfied these minimal criteria. One possible confusion, that surrounding the dual meanings of the word "Fair"- the judicial and the pigmental- was circumvented with a simple instruction to subjects that "Fair" was "in complexion, not in judgement". No subjects reported any difficulty with this instruction.

More rigorous testing was applied to the qualifying adverbs. It was necessary firstly to select adverbs which are reasonably well distributed along a dimension of "smallest to biggest", and also desirable that those ultimately selected should be adverbs whose relative position along this dimension is consistent across subjects. In a preliminary study, therefore 20 subjects were asked to place the adverbs "Extremely", "Very", "Rather", "Quite", "Fairly", "Reasonably", "Somewhat", "Moderately", "Slightly", "A little" and "Minimally" in rank order from that which they thought made the thing described "The biggest or most" to that which made the thing described "The smallest or least". The mean and standard deviation of rated position was then calculated and the five adverbs finally used were selected for both eveness of spacing along the magnitude dimension and consistency of rating. Full details of the eleven adverbs originally rated are provided in Appendix 1. Of the five qualifiers finally selected, their mean rated positions from 11 to 1 where 11 represents "Biggest or most", and the standard deviations associated with these positions were found to be: Extremely; 11.00, 0.00; Rather, 8.40, 0.516; Reasonably, 6.200, 0.789; Slightly, 3.00, 0.816; Minimally, 1.00, 0.000.

In a pilot study (see Appendix 1) these adverbs were combined with the adjectives "Happy", "Unhappy", "Calm" and "Excitable" in a person likeableness task (Anderson, 1983), using a pencil-and-paper visual analog scale. Three general findings were obtained: the rank order of the adverbs was preserved as above, parallelism was present in plots of the likeableness data, and the visual analog scale proved convenient and comprehensible to subjects. It was presumed that this pilot study provided justification for the use of the visual analog scale (transposed in the major study to an electronic touch keyboard), the selection of qualifiers, and the rather arbitrary choice of adjectives.

3.4 EXPERIMENTAL PROCEDURE.

The subject entered the experimental room and were seated in front of the black and white monitor, with the touch keyboard at the base of the monitor close to the hands of the subject. After the instructional set had been selected by the experimenter, the appropriate instructions were given to the subject to read. For all subjects, the instruction began as follows:

> This experiment is concerned with how people put information together. Your task is to rate how true each of a series of sentences is of you, from "not at all like me" to "exactly like me". The sentences are all very similar, so be sure to read each one carefully before making your judgement.
>
> Before each sentence appears you will hear a tone. This is your signal to direct your attention to the screen. Shortly after this the sentence will appear on the screen, where it will remain until you have made your response.
>
> Here is how to register your response. The keyboard in front of you is sensitive to touch. The left-hand end represents "not at all like me", the right-hand end "exactly like me". Simply touch the keyboard at any point between these two that you think corresponds to how true the sentence is of you.
>
> It is important that you respond to each sentence separately, without being influenced by your response to earlier items.

For those subjects receiving the "Global" Instructional Set, the instructions continued...

> ...Judge each sentence on the basis of your impression of how true the sentence as a whole is of you.

For those receiving the "Atomic Negative" instructions, this sentence was replaced with...

> ...Read each part of the sentence carefully and judge the sentence as true only if you believe that both parts of the sentence are true of you.

,while those receiving the "Atomic" instructions had:

> ...Read each part of the sentence carefully and make one rating of the sentence on the basis of how true you think

> each part is of you.

All instructions then concluded with:

> ...There will be a series of practice items before the experiment begins.
>
> Have fun, thankyou for being a subject.

The subjects were given sufficient time to read these instructions and asked if they had any questions. Before the practice trials were run, the instructions were repeated briefly by the experimenter, with the Set manipulation included in this description. For example,if a subject was assigned the Atomic Instructional Set, she was told:

> "O.K., so all you do is read the sentence when it comes along and make a single rating based on how true you think each part is of you"

A ten-item practice trial was then administered, using the adjectives "Tanned" and "Fit" and "Happy" and "Solitary", and the qualifiers "Very", "Moderately" and "A little", adverbs which had been rejected from the set on the basis of the pilot work described in section 2.3, yet which almost preserved the completeness of the magnitude dimension. Five stimulus items had the adjectives "Tanned " and "Fit", and five "Happy" and "Solitary". A key departure of this method from that advised by Anderson (1983) is the absence of stated end-anchors in the present study. This was due in part to the nature of the self-rating task- one cannot tell subjects a priori that any particular item is to be the most unlike them, nor that any item will be exactly the same as them- and in part to a slight conceptual difference between the city block metric being tested herein and an averaging model, as end anchoring commits a subject to a given item of maximum proximity to the self, while the geometric model allows for there to be no given item which exactly corresponds to the comparitor point. Rather than allocating a specific end anchor, therefore, in the present task subjects were encouraged to use the whole response scale and told that each end represented the extremes, and that they would be able to tell when they had seen the most extreme sentences. No subjects reported difficulties in anchoring their responses between the most extreme items they encountered for either the practice or the experimental trials.

Following the practice trials and checks that the subjects understood the requirements of the task, that part of the instructions containing the instructional set was once again repeated as described above and the experimental trail began.

A warning tone would sound, followed by a delay of 1.5 sec. before the stimulus appeared on the subject's screen. The item would then remain on the screen until either a response was recorded or a ten-second elapsed time expired, where would follow a 1 sec. delay prior to the warning tone sounding for the next stimulus item.

Stimuli were 72 sentences. Each stimulus consisted of either the adjectives "Dependent" and "Calm" (in that order) or "Tall and Fair" (in that order), with each adjective qualified by any one of the adverbs "Minimally", "Slightly", "Rather", "Reasonably" and "Extremely" or left unqualified. There were thus 6 possible qualifier conditions paired with the first adjective X 6 qualifiers of the second adjective X 2 adjective types = 72 items to be rated. The computer presented the stimulus items at random and recorded the subjects' responses through the Touch keyboard. The information recorded for each subject was whether a response had been made or the elapsed time expired, the positions of the left and right hand edges of the subject's finger on the keyboard, which was averaged and converted to a rating of between 0 and 100, a stimulus code, and the reaction time to the stimulus. For present purposes the RT values were not subject to analysis. The data was collected in a single session, after which subjects were debriefed and left the experimental room.

3.5 DATA ANALYSIS.

For the purposes of exploratory clarification of the additive (row + column) component of the data, the raw data was subjected to Median Polish (Tukey, 1977). This procedure enabled early examination of the independent row and column effects in each subject's 6X6 matrix, and thus a preliminary indication of the degree of additivity. The Median Polish was completed using the STATCALC statistical package.

Following the application of the Median Polish technique, data was subjected to preliminary model fitting intended for parameter estimation. Each subject's raw data was put through a Hookes-Jeeves pattern search programme. This sequential iteration programme was run first using the Averaging equation described in Equation 4, then the Euclidean Metric. On the basis of these two equations the estimation procedure produced an estimate of the sum of squared deviations from the model for each subject, a table of values expected under the model, and optimized estimates of the scale values of the six qualifier conditions, the subject's own position on the dimensions, and the relative weights of the two dimensions in the ratings. This primary analysis thus provided estimates of the goodness of fit of the two key models, together with estimates of those parameters upon which the models are based.

Following these two procedures certain modifications were made both to the models being fitted and the estimation device being used. A constrained optimisation function of the IMSL package was utilised to develop estimates of the degree of fit between the data and variously constrained versions of the Euclidean and Averaging models, and to produce "residuals matrices" representing the departure of the data from the model being tested. This phase of the analysis was more specfically concerned with attempting to improve upon and account for the extent of fit obtained.

Finally, the data were subjected to Analysis of Variance, of the form described by Anderson (1982). This comprises analysing not the data per se, but the matrix of differences between the observed and the expected values. The rationale for this is given on p195, 1982:

> The deviation scores for each subject are correlated through their dependence on a common set of parameter estimates. However, the deviation scores for different subjects are independent, since the model was fitted separately for each subject. Accordingly, repeated measurements analysis of variance may be applied to these deviation matrices.
>
> (1982, p195)

The prediciton under this residuals analysis of variance is that if the fit to the model is good, there should be no significant main effects nor any interactions in the results, that is, the prediction is that all variation from the predicted values will be random. All analyses of variance were conducted with the SPSSX package

Subsidiary analyses were conducted on the adjective type and instructional set variables. Use was also made of the curve fitting capacity of the Apple MacIntosh CricketGraph package.

This general process of analysis was common to all models fitted; departures from this process and elaborations upon specific procedures will be pursued further in Chapter Four.

CHAPTER FOUR: RESULTS

4.1 PRELIMINARY ANALYSIS: AVERAGING MODEL.

Factorial plots of all raw data for all subjects are depicted in Appendix III.

MEDIAN POLISH. As an initial investigation of the independence of row (adverb qualifying the first adjective) and column (adverb of second adjective) effects, Median Polish (Tukey, 1977) was applied to the data of all subjects. This technique, as performed by the STATCALC analysis package generates estimates of the percentage of variance explained by a simple row + column effect, as well as an estimate of the "typical value" , enabling a nonstatistical summary of complex data.

54 Median Polishes were performed, one for each adjective type for each subject. Estimates of the percent of variance explained by the row + column effect ranged from 8.99 (subject number 18, Tall, Fair condition) to 77.70 (subject 16, Dependent Calm condition), illustrating the high degree of between subject variation and a lack of uniformity in the experimental data. The distribution of these estimates across subjects for the Abstract and Concrete adjective types are depicted in figures 4.1 and 4.2 respectively:

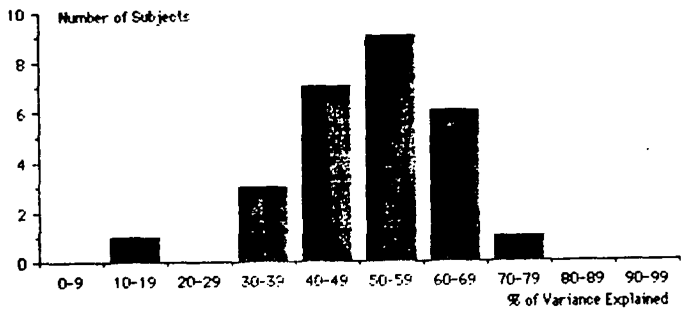


Figure 4.1 Distribution of Estimates of Variance Explained by ROW + COLUMN Effect Derived From Median Polish Technique "Abstract" adjective Type.

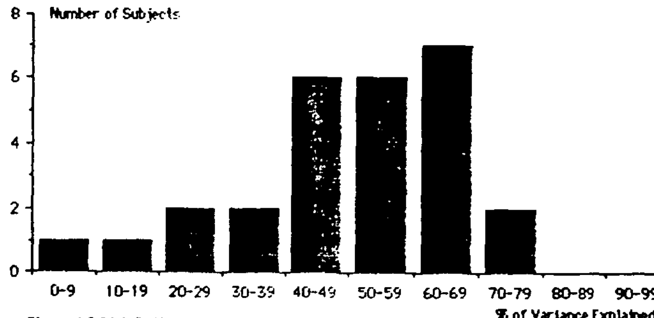


Figure 4.2 Distribution of Estimates of Variance Explained by ROW + COLUMN Efffects Derived from Median Polish Procedure "Concrete" Adjective Type.

Figures 4.1 and 4.2 restate the earlier observation that there is a large spread across subjects of the amount of variance explained by this extremely simple additive model; slightly greater for the "concrete" (tall, fair) than for the "abstract" (dependent, calm) adjective type. The mean percentage of variance explained for abstract adjective type is 52.80, while that for concrete adjective type is 50.29. The percentage of variance explained by the row + column effect for 36 random numbers between 0 and 1.00 is 35.79. While this contrast is by no means intended as a significance test of any sort, it is indicative of how little systematic effect of the type assessed by Median Polish there would seem to be in the experimental data.

PARAMETER ESTIMATION: AVERAGING MODEL. The application of the Hookes-Jeeves Pattern Search function to obtained data yielded parameter estimates of disputable value. Appendix II lists the estimates of all parameters for both adjective types under an averaging model in which the scale values of "Minimally" and "Extremely" are constrained to 0.00 and 1.00 respectively, with all other parameters free to vary between these values. This constraint was imposed for reasons discussed in the previous chapter - to substitute for the use of end anchors and to ensure relativity of weighting between the two adjectives.

For almost half of all data matrices (21 of the 54), the Pattern Search function failed in 500 iterations to find reliable convergence between the data and the averaging model, so the results from this analysis must be treated with caution.

Of those results obtained, however, certain features warrant note. Only eight subjects had comparitor values for "Dependent" that were higher than for "Calm"; that is, most subjects rated themselves as, in general, less dependent and more calm. Further, twenty-one subjects ascribed weights of 0.5 or greater to the first dimension in the "abstract" adjective case, that is, most subjects weighted "dependence" more highly than "calm" in producing their responses. By contrast, the items "Tall" and "Fair" seemed to be regarded more equally, both in comparitor points and in weighting. A little over half of the subjects rated themselves as more tall than fair (15 of the 27 subjects), and the same number ascribed weights of 0.5 or greater to the component "Tall" in their appraisal.

However, estimates of the sum of squared deviance from the model from this analysis were high and inconsistent, as can be seen by examination of the second column of Appendix II, indicating that the proximity of the data to the model is far from systematic, and not that which would be expected were the data to be consistent with the predictions of a different but closely related model, such as the Euclidean Model. The distribution of function values derived from this preliminary attempt to fit the Averaging model ranged from 0.07 to 4.21, with a mean of 1.02. There was a small difference between the mean function value for "abstract" adjective type (0.985), and that for the "concrete" adjective type (1.034), possibly indicating that data from the abstract adjective type provided a slightly better fit to the averaging model than that from the the concrete type. However it would once again be unwise to place any import upon this observation. An exact fit to the model would, of course, yield a function value of 0.00.

The substitution of the Euclidean metric for the averaging equation in this form of the model made no substantial difference to the consistency or clarity of the estimates obtained.

The manifest lack of parallelism in the factorial plots of the data, coupled with the inconclusive findings of this parameter estimation procedure resulted in a decision to proceed with the development of the model and improvement in the estimation procedure rather than to persist with parameter estimation for both the averaging and the Euclidean model.

4.2 SECONDARY MODEL FITTING: AVERAGING AND EUCLIDEAN MODELS

It was decided on the basis of the failure of the parameter estimation procedure that subsequent analysis should concern only improving the goodness of fit of the models to the data obtained. One observation from the parameter estimates of the preliminary run was that for several subjects the estimated scale values of the qualifiers were in an order different to that suggested by the pilot study (see appendix I). While this is entirely consistent with the within-subject nature of the task, and quite allowable for the purposes of parameter estimation, certain of these reversals seemed unusual from common English usage: such as the subject who appeared to have ascribed the qualifer "Slightly" a value above that estimated for either "Reasonably" or "Rather". It was suspected that at least some of these reversals may have been due to either random error or some nonrandom distortion of the scale from linearity. In either case to constrain the 6 qualifier conditions to the order, in ascending magnitude, of "minimally", "slightly", "reasonably", "rather", unqualified and "extremely" would render the data more accessible to interpretation. As can be confirmed from Appendix II, the imposition of this constraint would alter the rank order of the qualifier estimates in 25 of the 54 matrices.

The ZXMWD routines of the IMSL package were utilised for these later analyses. The iteration procedure defined for the present data continues until 2010 iterations have been reached, provided slightly greater analytic power than did the Hookes -Jeeves function. It was also felt that the IMSL package, contained in a Pascal programme would more efficiently handle the repeated changes and modifications required for these later optimisation runs.

Placing this constraint upon the scale values of the qualifiers produced substantially lower and more consistent function values, though this must in part be due to the impostion of the constraint itself. As the present concern is only with minimisation of the function values rather than parameter estimation, only function values shall be discussed.

Table 4.1 represents the function values (sums of squared deviations from the values expected under the model) obtained when this new optimisation function is applied for both the Averaging and the Euclidean models and both types of adjective.

TABLE 4.1. FUNCTION VALUES FOR EUCLIDEAN AND AVERAGING INTEGRATION MODELS, SCALE VALUES OF QUALIFIERS CONSTRAINED FUNCTION VALUE

	AVERAGING MODEL		EUCLIDEAN MODEL	
SUBJECT	ABSTRACT	CONCRETE	ABSTRACT	CONCRETE
01	0.06	0.41	0.05	0.34
02	1.20	0.51	1.20	0.51
03	0.55	0.39	0.55	0.35
04	0.28	0.30	0.30	0.19
05	0.41	0.59	0.38	0.54
06	1.29	0.70	1.02	0.65
07	0.38	1.19	0.39	0.52
08	0.77	1.02	0.78	0.81
09	0.40	0.70	0.36	0.65
10	0.51	0.38	0.46	0.20
11	1.37	1.17	1.37	0.85
12	0.57	0.73	0.54	0.56
13	0.60	1.11	0.52	1.13
14	1.00	0.31	0.83	0.35
15	0.64	0.39	0.44	0.23
16	0.45	0.95	0.38	1.17
17	0.94	0.78	0.90	0.65
18	1.30	0.67	1.21	1.03
19	1.70	0.66	1.61	0.99
20	4.26	2.63	3.90	2.37
21	1.03	0.97	0.80	1.15
22	1.44	1.87	0.99	1.40
23	0.65	0.44	0.40	0.46
24	0.54	0.66	0.55	0.84
25	1.08	0.37	1.01	0.58
26	0.86	0.80	0.78	0.78
27	1.88	0.69	1.61	1.12
Mean Adjtype Function Value	0.97	0.79	0.86	0.76
Mean Model Function Value	0.88		0.81	

It would seem from this estimation that for both models the concrete adjective condition provides a closer fit than does the abstract adjective type, with a mean difference of around 0.15. This constitutes a reversal of the suggestion from the preliminary fit, however it is possible that both of these differences may be attributable to random error. There is also a small mean difference for model type, with the Euclidean metric, in general, providing a slightly better fit to the data than does the averaging model, though once again no claim shall be made as to the substance of this difference at this stage.

A third and subsequent change in estimation procedure involved estimation of the origin of the response scale - corresponding to an unweighted Initial Value in Anderson's 1983 terminology, or the S_o term in Equation 3. The origin was included for both the additive and the euclidean functions as an additive constant. The inclusion of the origin of the scale as a parameter to be estimated altered the funtion values derived for only four of the 54 matrices - all others had estimated origin values. For those matrices that had nonzero origin estimates, this value was always less than 0.45. It was felt therefore that the inclusion of the origin as a parameter made no substantive change to the goodness of fit of the observed value under either model. It was thus the expected values under the assumptions of the previous model - constraints upon the qualifier values but without estimation of the origin - which were used in the Residuals Analysis of Variance (Anderson, 1982).

4.3 RESIDUALS ANOVA: AVERAGING AND EUCLIDEAN MODELS.

The "replications method" ANOVA Anderson (1982) involves the use of the Analysis of Variance tachnique in order to assess the extent of departure of the obtained data from those values expected a stated model. By utilizing the deviations of observed from expected scores rather than raw data, it becomes possible to meaningfully describe trends in data across subjects. While parameter estimates can freely differ across subjects, the discrepancy between observed and expected data should always be random if the data fits the model. Thus the expectation of the replications model ANOVA is that all departures from zero are random; that is, there should be no significant main effects or interactions over all residuals matrices.

For the present data, residuals matrices were produced for both the Averaging and Euclidean models across both adjective types and all Instructional Set conditions. This yielded a 6 (qualifier of the first adjective) X 6 (qualifier of the second adjective) X 2 (Adjective type) X 3 (Instructional Set) replications ANOVA, in which only Instructional Set exists as a between-groups term. The "null hypothesis" thus represents nonsignificant departure from the model, under all conditions of adjective type and instructional set.

For the averaging model the replications ANOVA produced significant Main Effects for First Qualifier ($F = 25.16$, 5df, $p < 0.01$) and Second Qualifier ($F = 24.63$, 5df, $p < 0.01$). There were significant two-way interactions between First qualifier and Second qualifier ($F = 8.75$, df25, $p < 0.01$), Instructional Set and Adjective type ($F = 5.75$, df2, $p < 0.05$), and Second Qualifier and Adjective Type ($F = 33.52$, df25, $p < 0.01$). The three way interaction of First Qualifier X Second qualifier X Adjective type was also significant ($F = 1.76$, df25, $p < 0.05$). There was a marginally significant Main Effect for Adjective type ($F = 3.77$, df1, $p = 0.06$).Figures 4.3 and 4,4 overleaf depict the Main Effects for First Qualifier and Second Qualifier respectively, while the interaction between these factors is represented in Figure 4.5.

As can be seen in Figures 4.3, 4.4, and 4.5, the departure of the data from the averaging model is not random, but shows a distinct quadratic and possible cubic trend- with the observed values initially less than expected values for the qualifier "minimally", drawing closer to and often overestimating the model for the intermediate items, and finally falling well below the expected values for the qualifier "extremely". It would also appear that there is a more prominant cubic component to the

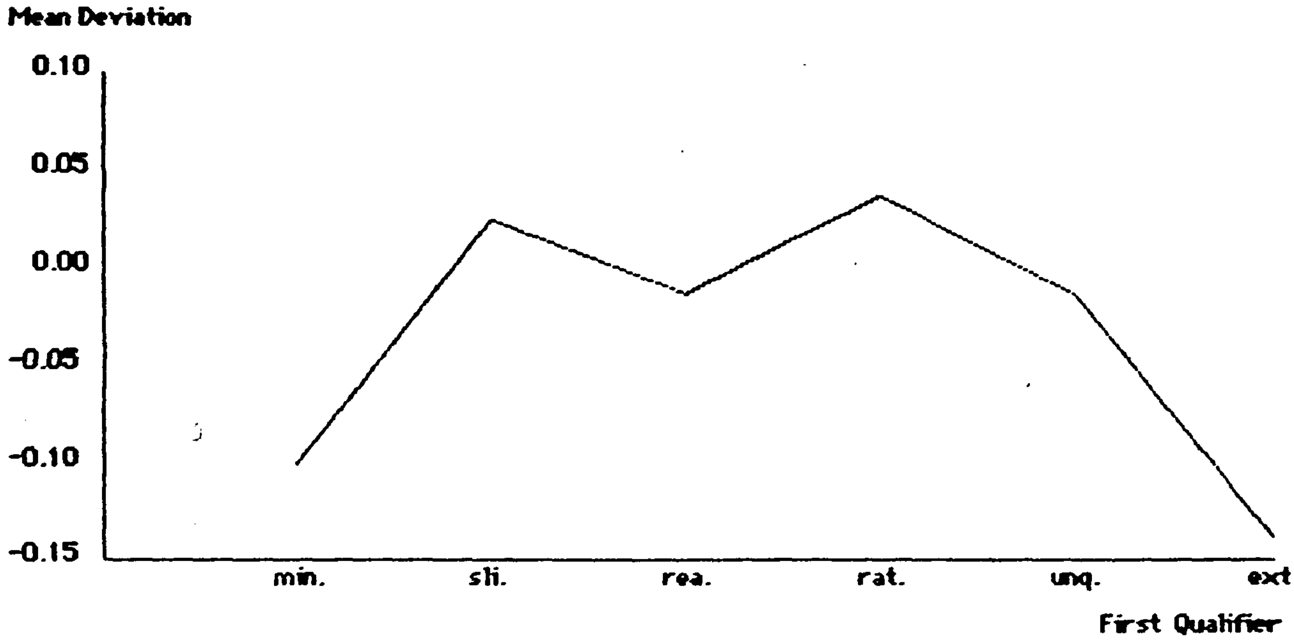


Figure 4.3. Main Effect for First Qualifier, Averaging Model

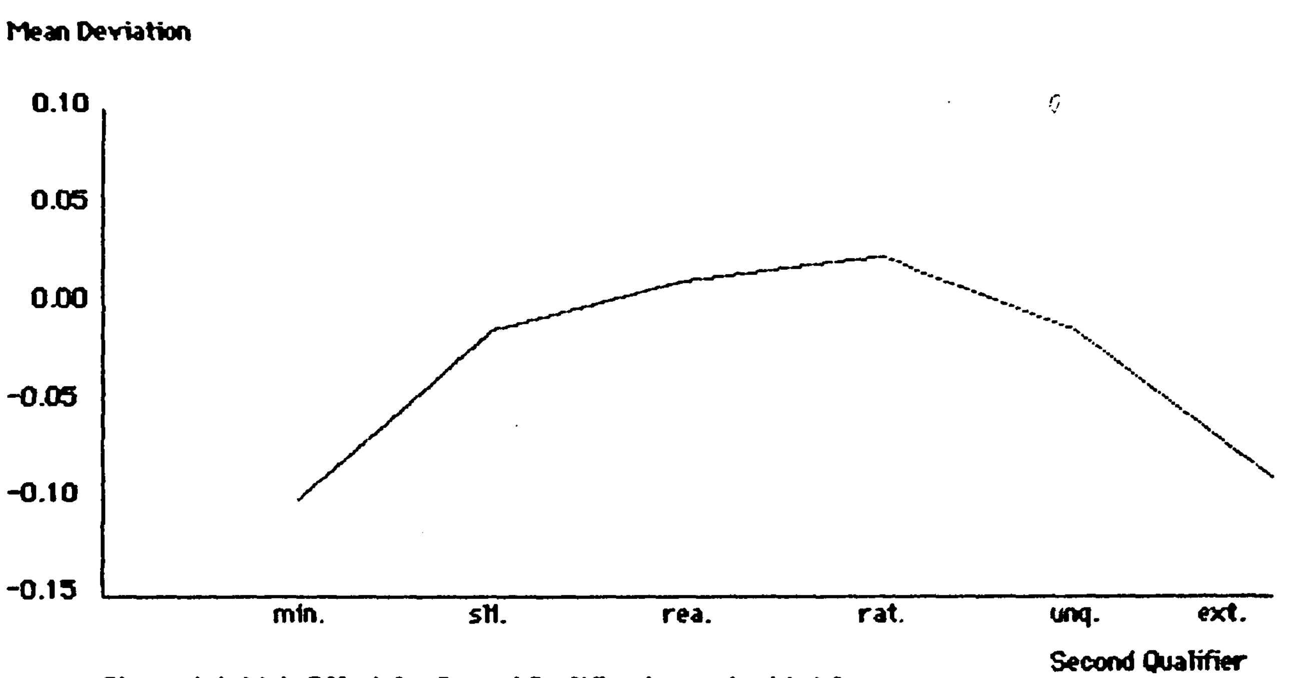
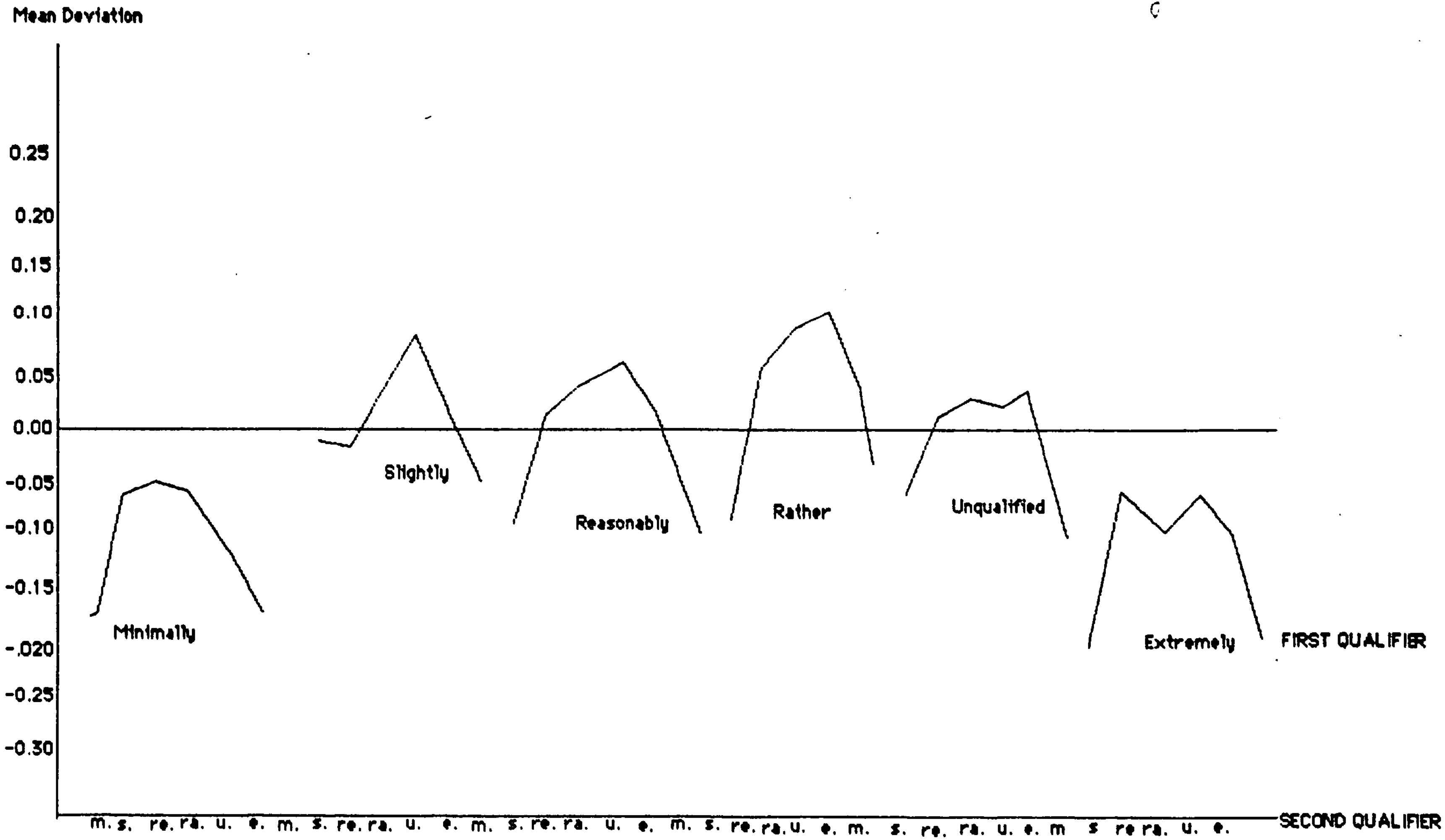


Figure 4.4. Main Effect for Second Qualifier Averaging Model



m. =minimally ,s. =slightly, re.=reasonably, ra.=rather, u.=unqualified, e.=extremely

Solid line through zero on the vertical axis represents perfect fit

Figure 4.5 First Qualifier by Second Qualifier Interaction. Averaging Model.

deviation matrix for the second than for the first qualifier, a suggestion borne out to some degree by the CricketGraph Curve fitting procedure.

The interaction graph (figure 4.5) indicates that, as well as the foregoing, there is a systematic change in the curve for the first qualifier as a function of changing the second. Again the more extreme items- minimally and extremely- seem to produce deviation scores which contain a greater quadratic component than do the remaining qualifier conditions.

The replications ANOVA performed using matrices of deviation from the euclidean model produced strikingly similar results. Significant main effects were once again found First qualifier ($F = 10.88$, 5df, $p < 0.01$) and Second Qualifier ($F = 9.59$, 5df, $p < 0.01$). For the Euclidean model, Adjective type also showed a significant main effect ($F = 5.96$, 2df, $p < 0.05$). The two-way interactions of First Qualifier X second Qualifier ($F = 4.09$, 25df, $p < 0.05$), Instructional Set and Adjective type ($F = 7.25$, 2df, $p < 0.05$) and Second Qualifier X Adjective Type ($F = 13.01$, 5df, $p < 0.01$) were once again significant, as was the First Qualifier X Second Qualifier X Adjective Type three-way interaction ($F = 1.75$, 25df, $p < 0.05$). Figures 4.6 and 4.7 depict the main effects for the First and Second qualifiers and, 4.8 depicts the interaction between them under the expected values of the euclidean model.

Figure 4.6 Main Effect for First Qualifier. Euclidean Model

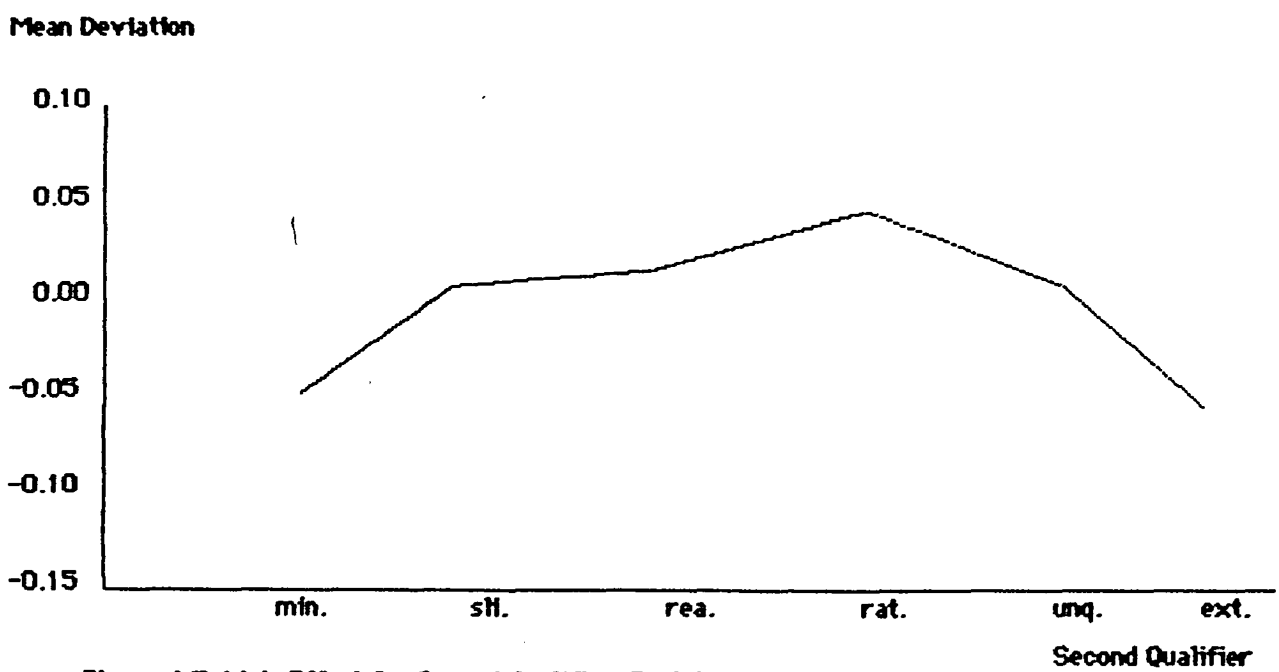
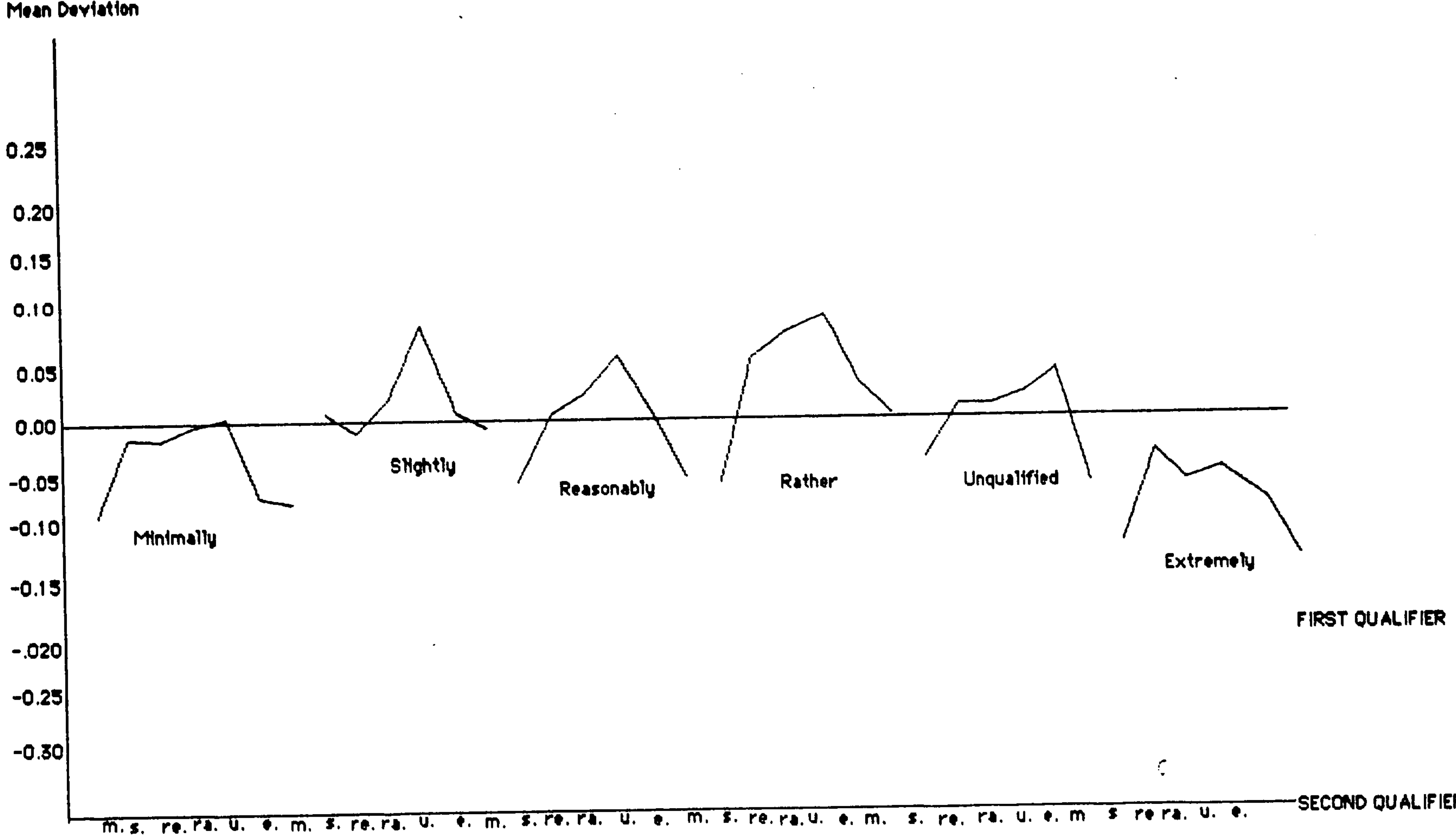


Figure 4.7. Main Effect for Second Qualifier. Euclidean Model



m. =minimally ,s. =slightly, re.=reasonably, ra.=rather, u.=unqualified, e.=extremely

Solid line through zero on the vertical axis represents perfect fit

Figure 4.8. First Qualifier by Second Qualifier Interaction. Euclidean Model

Similar comments apply to these results than to those for the averaging model. Both Main Effect curves indicate both quadratic and cubic trends in the data, and the interaction graph shows the form of changes in the first qualifier curve over changes in the second.

One general difference between the Averaging and Euclidean Residuals ANOVA, however, is in the absolute level of the deviations observed. While for both models the data significantly underestimates then overestimates then underestimates the expected values, the numerical magnitude of these Main Effects is much less for the euclidean the for the averaging model. There is also a difference in the interaction plots, with the Euclidean model generally producing more positive residual values, suggesting that the ratings produced are more often higher than those expected for this model than for the averaging model. This difference between models, both the smaller magnitude of deviation and the greater positivity of deviations for the euclidean model must be atrributable to differences between the two models. As discussed in Sect. 2.3, the key difference between the Euclidean and the Averaging models is in the VARIMIN function of the Euclidean model, which would predict a "clustering" of values toward the more extreme scale values. This may suggest that there was a degree of such "clustering" in the raw data, a finding which would be consistent with a disproportionate weighting of extreme values, as shall be discussed in Chapter 5.

ADJECTIVE TYPE AND INSTRUCTIONAL SET. The inclusion of Instructional Set and Adjective Type as factors in the residuals ANOVA permits investigation into the degree to which these manipulations influence the goodness of fit to the two models(see Sect. 2.4). The marginally significant Main effect for Adjective Type under the Averaging model, and the significant Main effect for the same factor under the euclidean model are depicted in figures 4.9 and 4.10 respectively and the interaction between Adjective Type and Instructional set for the averaging and euclidean models are shown in figures 4.11 and 4.12 respectively. Figures 4.13 and 4.14 represent the significant interaction between Second Qualifier and Adjective Type for , respectively, the averaging and euclidean models.

4.4 THE AVERAGE SUBJECT.

Anderson (1982) cautions against the use of mean responses for the purposes of assessing additive models. However this concern is centred more upon validity of parameter estimates than of general goodness of fit of the data. The ANOVA results suggested effects which are not visible in the raw data plots, so it was decided that examination of the mean ratings and deviation scores provided the next appropriate step in explanation of the data. The use of mean results must, of course be tempered by the proviso that the matrices so obtained are not representative of

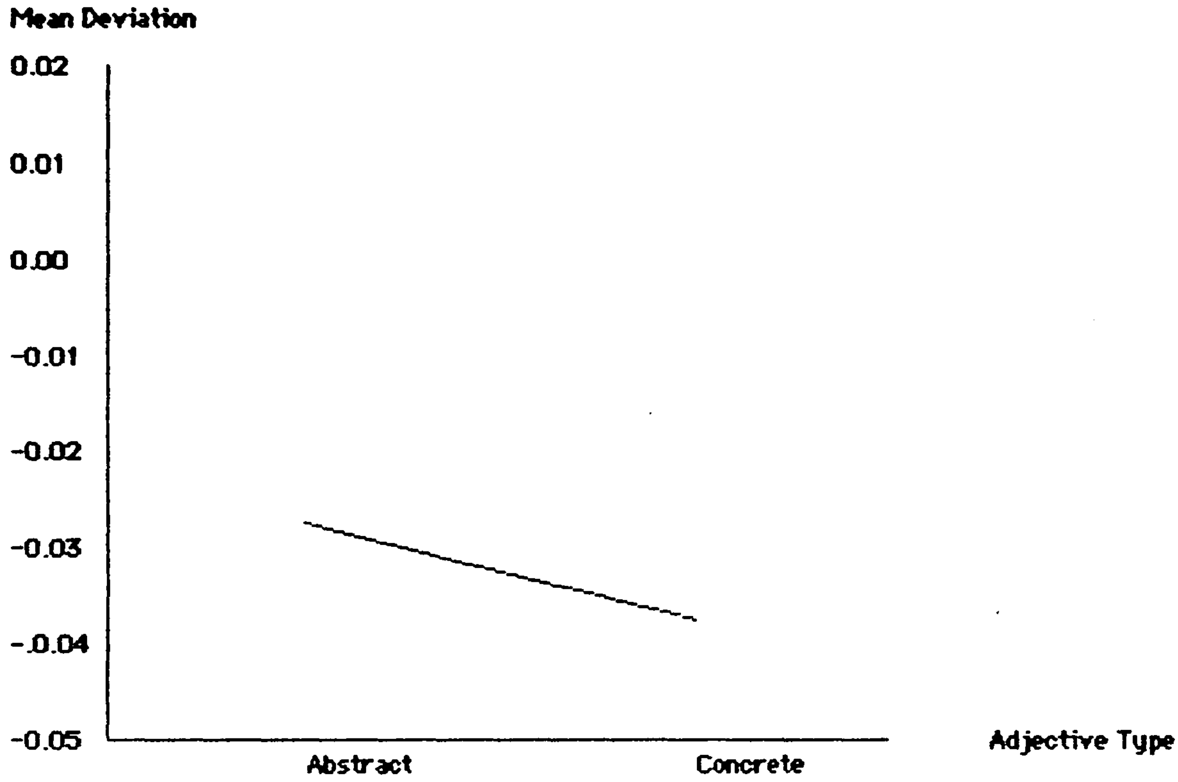


Figure 4.9 Main Effect for Adjective Type. Averaging Model

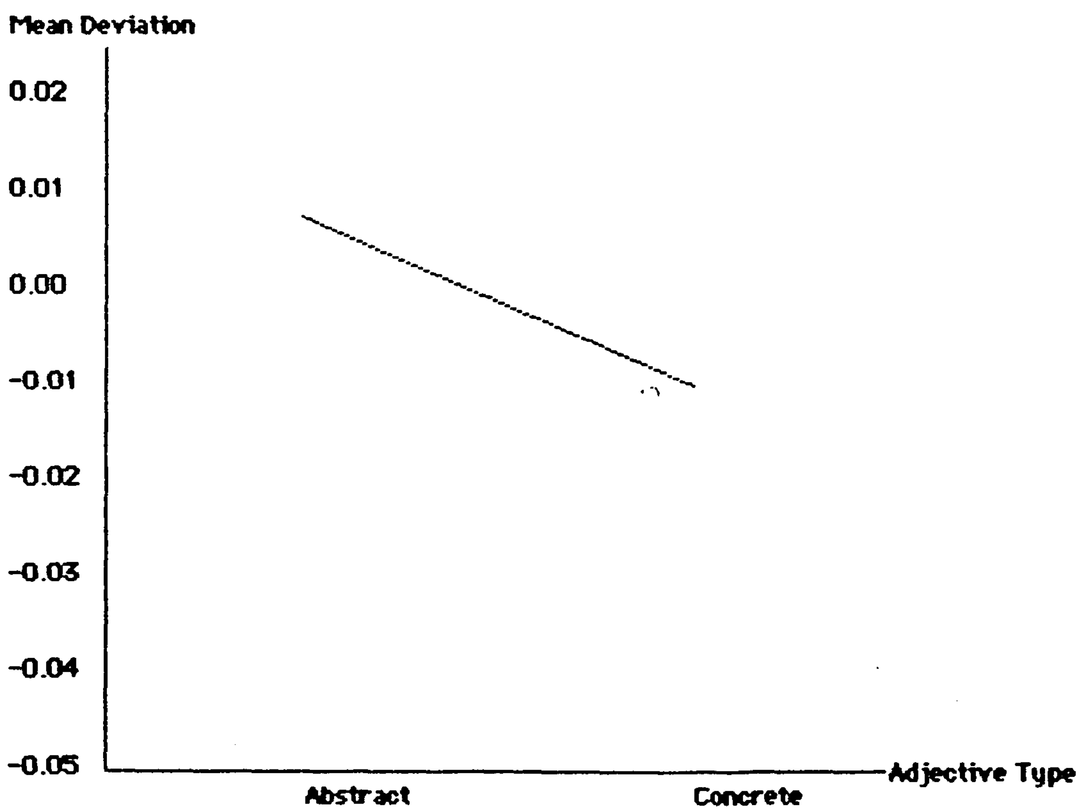


Figure 4.10. Main Effect for Adjective Type. Euclidean Model

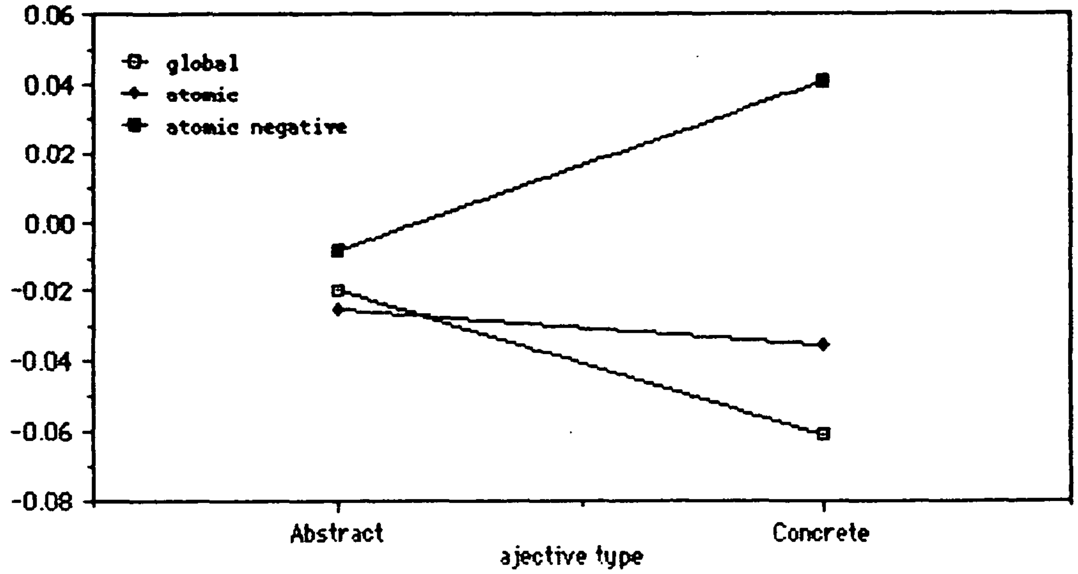


Figure 4.11. Instructional Set by Adjective Type Interaction. Averaging model

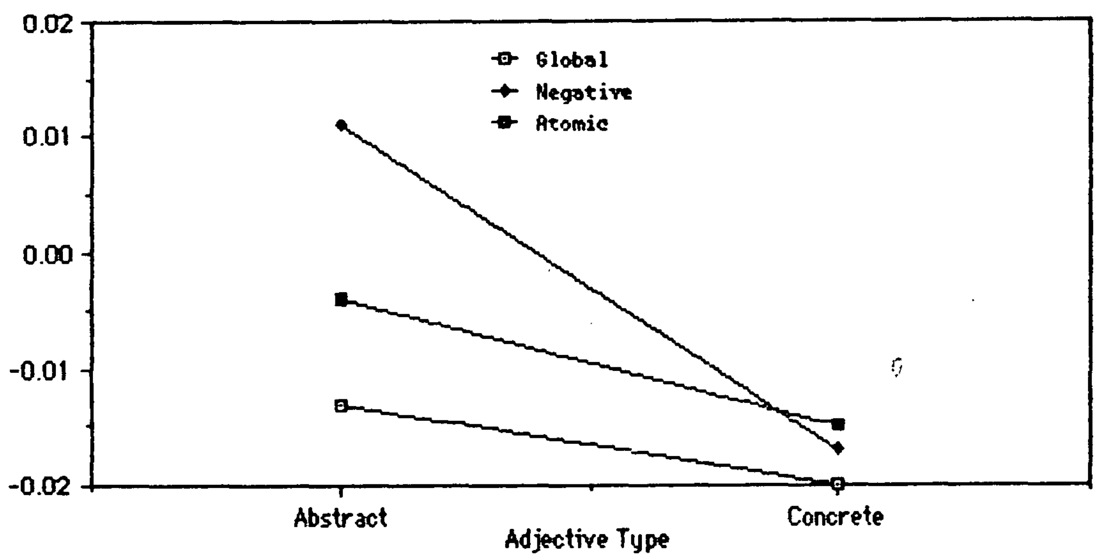


Figure 4.12 Instructional Set by Adjective Type Interaction. Euclidean Model.

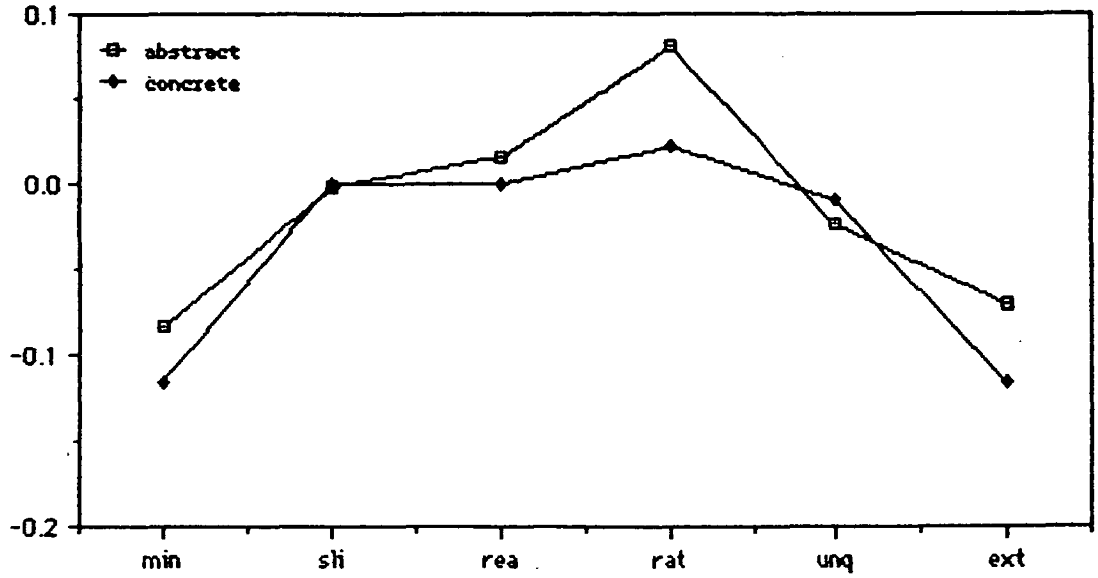


Figure 4.13. Adjective Type by Second Qualifier Interaction. Averaging model

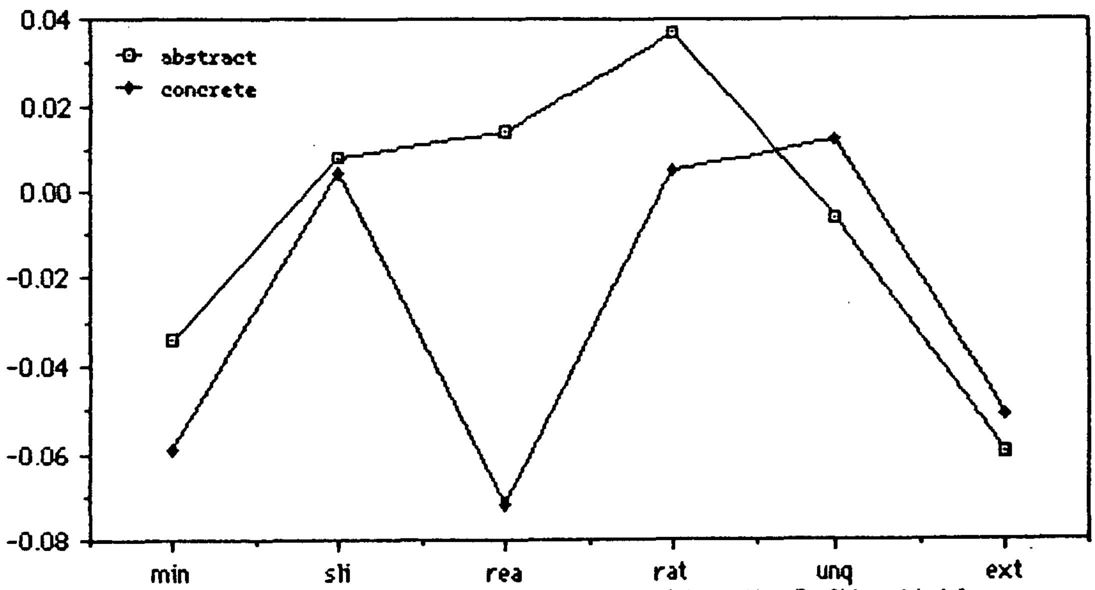


Figure 4.14. Second Qualifier by Adjective Type Interaction. Euclidean Model

the performance of any experimental subject. Figure 4.15 is factorial plot, similar to those in Appendix III, of averaged responses to each of the 72 items. Responses are also averaged over adjective type, producing the 36 point plot depicted.

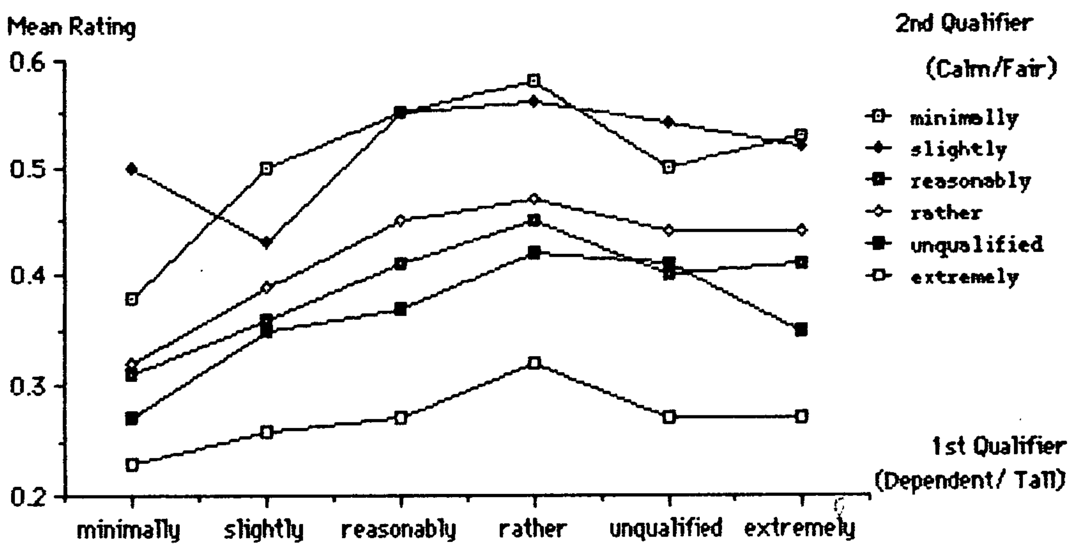


Figure 4.15. Factorial Plot of mean Rated Responses . N=27. Both Adjective types

By "ironing out" the individual subject variation, figure 4.15 reveals certain features of the data that have alredy been discussed in less specific terms. It would suggest that there is indeed a general parallelism in the data obtained, as well as evident systematic departures. The curves for qualifiers "slightly" and "reasonably", for instance, seem to decline under those circumstances where the second qualifier is "extremely", where all other curves increase in value.

There is also some visible evidence of the curves spreading apart a little through the intermediate values and drawing closer together at the extremes; a suggestion also made from the ANOVA results.

By submitting this averaged data to the same iteration procedure as described in Sect. 4.2, function values for both the averaging and the euclidean models were generated, together with matrices of the residuals for these models. The function value of the averaged data under the averaging model is 0.187, while that for the euclidean model is 0.090, adding some support to out earlier indications that the euclidean model provides a slightly better fit to the obtained data than does the averaging model. Figure 4.16 is a plot of the deviation of each mean rating from the value expected for that rating under the averaging model. Figure 4.17 is the deviation of the mean ratings from those expected under the euclidean model.

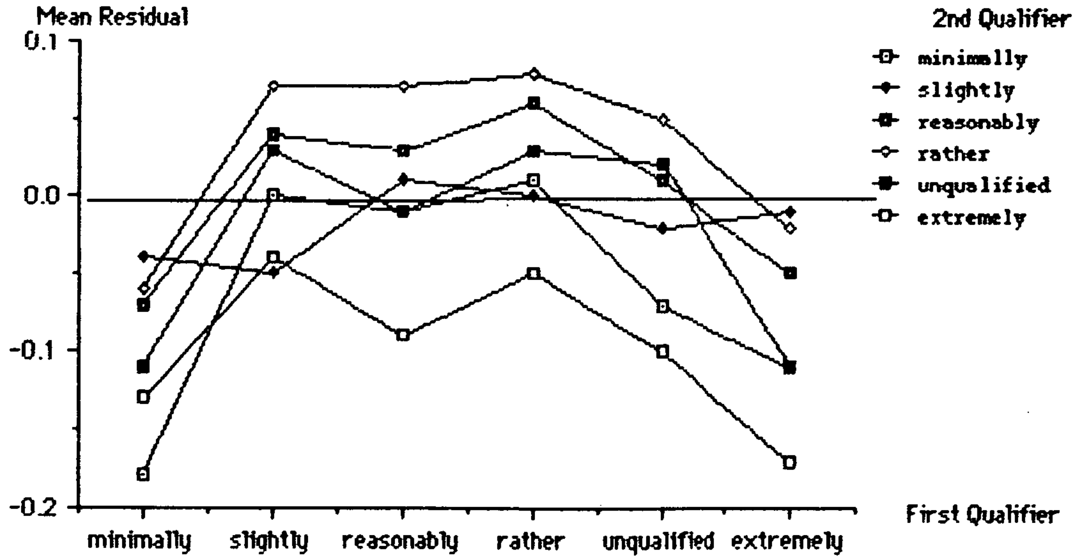


Figure 4.16. Residuals Derived From Mean Ratings. Averaging Model

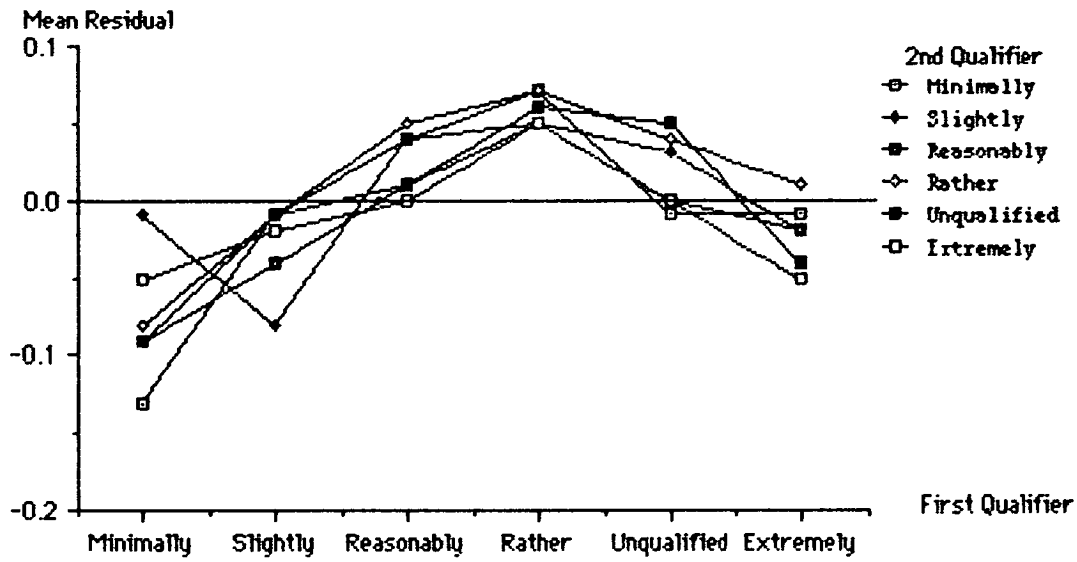


Figure 4.17. Residuals derived From Mean Ratings. Euclidean Model

The solid line through the zero point of figures 4.16 and 4.17 represents the expected values for an exact fit to the model.

Again the curves shown in figures 4.16 and 4.17 provide a degree of support for findings suggested elsewhere. It would seem that there is some validity in concluding that the data shows generally less deviation from the euclidean than from the averaging model, and that the deviation values are more typically positive for the former than for the latter. There is also less crossing over of curves in the euclidean mean residuals plot than it that for the averaging model, suggesting that this model predicts more consistently the effect of the second qualifiers over levels of the first. The euclidean model would also appear to reduce the absolute of spread of the six curves , a manifestation of the VARIMIN function described previously. The euclidean model therefore provides the better approximation to the data obtained than does the averaging model.

It must be borne in mind, however, that Figures 4.15, 4.16 and 4.17 are derived from an essentially hypothetical data set in which each response is equal to the mean value of that response across all subjects and both adjective types. Examination of Appendix III demonstrates strikingly that subjects did not consistently obey any compelling integration rule, and the departure of the subjects responses from the parallelism or near parallelism predicted under the averaging and euclidean metrics respectively is as much a feature of the data than whatever consistencies may show up in the mean ratings.

4.5 SUMMARY OF KEY EXPERIMENTAL RESULTS.

Neither the averaging nor the euclidean model adequately predicted the experimental data, as evidenced both by high and inconsistent function values from model fitting and by a number of significant main effects and interaction terms in the replications method ANOVA.

It is suggested that despite the significant departures from both models, the euclidean model provides a better approximation to the data than does the averaging model, evidence being derived from the estimated goodness of fit, the deviations matrices of the residuals ANOVA, and examination of plotted residuals derived from mean ratings. This difference would appear due to the prediction by the euclidean model that extreme items shall be valued more highly than intermediate items.

CHAPTER 5. DISCUSSION AND CONCLUSIONS

5.1 HYPOTHESES OF THE PRESENT STUDY.

In the light of the failure of the data obtained to correspond satisfactorily to either the averaging or the euclidean models, certain important features of the Valuation, Integration and Response functions as described by Anderson, (1981) must be reconsidered and possibly revised.

It is known from the pattern of significant effects in the residuals ANOVA that the data obtained is significantly nonrandom (see Sect. 5.4) ,and thus it becomes necessary to examine possible sources of the systematic variation of the data from both the averaging and the euclidean models.

For the purposes of the present study, certain expectations were held concerning all stages of judgement formation. It was hypothesised that Valuation- the ascription of a scale value and a weight to a component of a compound stimulus- could be regarded as the dual processes of i. estimating the proximity between the given item and some fixed comparitor point, and ii. ascribing a multiplicative constant to the dimension on which the given component lies, that is, weighting the dimension. It was also expected that the weight so ascribed would be constant across the length of the stimulus dimension, and that the weighting of the two dimensions in the compound would sum to 1.00.

The present study also tested two possible Integration processes that could occur once valuation had taken place; the averaging model of Anderson (1965, 1981), in which rated judgements are equal to the summed weighted values of the components, and an alternative euclidean model in which the response is seen as equal to the square root of the summed squared weighted scale values of the components. The geometry and mathematics of these two models are described in Sects. 2.2 and 2.3.

Finally, the Response function was also investigated, albeit less centrally. The use of the visual-analog scale in the form of an electronic touch keyboard was a methodological development of the present study. It was assumed on the basis of pilot work and face validity that such a scale would preserve linearity and consistency of responses, that is, that the response device would not itself interfere with the judgement produced by the valuation and integration processes. Each of Valuation, Integration, and Response will be discussed in turn before any general conclusions are drawn.

5.2 THE GEOMETRY OF VALUATION: DIFFERENTIAL WEIGHTING.

Valuation is the process by which each component of a compound stimulus is given a numerical value to be subsequently combined by the Integration function. This value comprises two independent parts : a scale value of the component- in the present experiment correponding to an estimate of the linear proximity of, for example, the item "extremely calm" to a point at which the subject would freely place herself, or the comparitor point, on a conceptual dimension reaching from "zero calm" to "infinity calm": and a weight - corresponding to the relative importance of "Calm" in a rating when combined with "Dependent". Under the two-component conditions of the present experiment, the space in which valuation and integration occurs was expected to be two-dimensional. This description of the valuation process was common to both the averaging and the euclidean models. Critical to this description of the valuation process is the constancy of weighting along the length of the dimension. Nonconstant weighting is inconsistent with the two-dimensional analogy made herein, as it effectively results in each compound stimulus item occupying a different set of axes. One cannot predict, under differential weighting, the proximity of two points in space from the proximity of each of those points to a number of other points, as there may be a substantial change in relative weighting intervening.

Problems in producing generalisable functions for differential weight models have been discussed in the literature for some time. Oden and Anderson (1971) attempted to test a differential weight averaging model in judgements of seriousness of criminals, favourableness of meals, and effectiveness, respect, and liking for naval officers by assuring preservation of constant weighting in one dimension, thus enabling comparison of this weight to the weighting of the other items at various stimulus levels. They found, however, that while the general pattern of judgements supported an averaging model, the differential weighting was less clear, and only detectable in the form of departures from parallelism. In comparing differential weight and constant weight models, they write:

> Differential weighting unfortunately produces nonlinearities in the response-stimulus relation because the weights enter the denominator of the averaging equations. [see Equation 3]. However, simple analyses are available if equal weighting can be maintained within one factor of the design...
>
> (p.160)

In the present experiment, of course, no methodological attempt was made to preserve constancy of weighting along either dimension - such constancy was assumed for the purposes of model analysis. It cannot be ascertained, therefore, whether either, both, or neither dimension in each compound preserved constancy of weighting for all levels of the stimulus dimension.

It is fruitful, nonetheless, to briefly examine, in the light of the present results, models of judgement which predict differential weighting of particular items in opinion formation, particularly those models which predict some change in the valuation of items as a result of item extremity.

Anderson (1981) says of the effects of negativity and extremity in judgement that:

> A negativity effect means that negative information has greater importance than positive information or, more generally, that importance is an inverse function of scale value. An extremity effect means that importance is a direct function of scale value. Within averaging theory, negativity and extremity effects reflect weight parameters that are not constant, but instead are correlated with scale value. These effects are thus special cases of differential weighting
>
> (p.275).

Several judgement theorists have investigated the extent to which the extremity of a rated item influences the weighting of that item in the compound. The Congruity model of Osgood and Tannenbaum (1955), for instance, predicts that the weights of the components of a compound stimulus are distributed in proportion to their scale values - that is, that weight is differentially distributed by importance. A prediction drawn from this by Warr and Jackson (1975) is that, set against a constant standard point, increasing the value of the more important component in the compound will increase the weight of that component. Using ratings of contingency - how likely it is that a person would be A as given that she is B- disconfirmed the above predictions of the congruity model, supporting instead an alternative Range Adjustment model, in which a standard starting point, representing the more important component is adjusted back by a constant representing the less important component. They suggest from this that increasing the extremity of a component has minimal effect upon the weight of that component until such a time as a qualitative cognitive change in the nature of the nature of the judgement occurs. Warr and Jackson (1975) conclude that:

> ...extremity is of general importance in compound judgement but that increasing extremity does not yield greater importance until the judgement becomes one of certainty.

The findings of Warr and Jackson, however, represent an atypical result for extremity studies, in which it is usual to find differential weighting of extreme items, and may be subsumed by a more general extremity weighting model, the only key feature of the Warr and Jackson (1975) findings being the swift change in weighting observed at high levels of extremity.

Manis, Gleason and Dawes (1966) produced extremity weighting effects across a range of social judgements. Anderson and Alexander (1971 reinterpreted by Anderson, 1981) identified deaprtures from parallelism consistent with extremity weighting in person perception judgements. Anderson (1981) discusses at some length the problems extremity and negativity rating pose for an adding or averaing integration model.

There is some evidence that the departures from the euclidean and averaging models in the present experiment may have been due in part to an extremity weighting valuation function, with the qualifiers "minimally" and "extremely", particularly "extremely", creating extreme points on the rated dimensions which are then weighted more highly by the Valuation function than less extreme points. This would result in the distances between items at these extreme points being greater than at intermediate points along the dimensions. Proximity estimates would thus be generally lower at the extreme qualifer levels than at all others. This is a feature visible both in the individual subject plots of Appendix III and in the averages plot of Figure 4.17.

A second suggestion derivable from extremity weighting concerns the nature of the departure of the data from the values expected under a constant-weight averaging model. As stated earlier, the extremity weighting model would predict that the rated similarity to self would in general be lower for extreme than for non-extreme components. These ratings would also be lower than those expected under the constant weight averaging model, that is, extremity weighting model would predict in the context of the present experiment that the ratings observed will typically be lower than those expected under the averaging model at the "Minimally" and "Extremely" ends of the scale for each of the first and second qualifiers. This prediction also finds some support in the curves for the main effects within the residuals for the first and second qualifiers for both the averaging and euclidean models (Figures 4.3, 4.4, 4.6 and 4.7) .

Finally, a form of support for a valuation function in which weight and scale value are correlated can be seen in the ancilliary finding that, although depatures from both were significant in the present study, the magnitude of the difference between the observed and the expected values was generally a little lower for the euclidean than for the averaging model. As discussed elsewhere (sect.2.6, 4.4) the central difference between the averaging and the euclidean models is the prediction from the latter that, as the scale values become more equal, the proximity estimates between points shall increase. This is tantamount to a prediction that ratings for extreme values shall be typically somewhat lowere than for intermediate values, as well as more clustered. That the euclidean model seemed, in general, to align somewhat more closely with the data than did the averaging model may be due to the manner in which the former mimics the predictions of a differential weight averaging model in which weight increases with extremity. This is further evidenced by the observation that the shape of the departure of the data from the euclidean model is essentially the same as that for the averaging model. That is, the euclidean model also overestimated the proximity ratings at the extreme ends of the scale, allowing the possibility that the failure of this model was due to its relative "underestimation" of the extremity effects, while its general superiority to the averaging model is due to its mimicry of them.

It must be remembered however, that there was significant departure of the data from the euclidean model, and the evidence for extremity weighting in valuation is no stronger than that for a euclidean integration function. It is impossible, therefore, to conclude whether the results obtained support a constant weight valuation coupled with an unknown integration rule, or an extremity weighting valuation function operating within an averaging-like integration procedure.

5.3 THE GEOMETRY OF INTEGRATION; AVERAGING AND EUCLIDEAN MODELS.

The results of the present study provide no compelling support for either the constant weight averaging model nor the euclidean model of information integration. Factorial plots of the subjects' data (Appendix III) reveal gross lack of parallelism, and the mean ratings plot (figure 4.15) shows that, even with the within-subject variation averaged, there is still serious departure from parallelism. This departure goes over and above the pattern of results cited above as possible evidence for an extremity weighting valuation function. The crossing over, for example, of the curves for qualifiers "minimally" and "slightly" in the plot depicted in figure 4.15, is a finding which has no explanation within a constant weight averaging or euclidean integration model. The only clear conclusion that can be drawn regarding the integration function utilised for self-rating in the present study is that it would appear to be neither averaging nor euclidian but that there is, however, is evidence that whatever the function is, it is more simlilar to a euclidean than to an averaging model.

One of the central purposes of the study- to investigate the extent to which schemata and self-rating can be viewed as the generation of proximity estimates in N-dimensional space would seem thus unresolved. Certainly the simplistic geometric alternatives presented in Chapter 2 have not been supported by the results of the present experiment. A question which must therefore be asked is could self-rating be a geometric task of the type described in chapter 2 without obeying either a city-block nor a euclidean metric? The answer, certainly is yes. Even if the process of valuation is precisely as described in Sect. 2.2 - calculation of the proximity of the stimulus to a comparitor point in 2-dimensional space, there are a potentially infinite number of ways in which the distance between the two points defined could be calculated. However, the city block, adding-type metric and the euclidean metric certainly represent the most obvious of the alternatives, and the failure of these two models would seem to hold little hope for any more complex or sophisticated models, and therefore for a general N-dimensional geometric interpretation of self-rating.

Shepard (1962) discusses the general use of multidimensional scaling in the analysis of proximities in spaces of unknown dimensionality, however the design of the present experiment lacks the power for these multidimensional analyses.

The results of the present study thus provide falsification of the geometric rendition of self rating as stated in chapter 2, as well as indicating a failure of the equal weight averaging model (Anderson, 1981) to adequately predict performances on a self-rating task. No affirmative evidence can be gained, however , as to which integration function is used for this type of rating, although, as discussed previously, a case can be made for the operation of an averaging integration function if coupled with an extremity weighting valuation function, however even this explanation cannot account fully for the crossing over of curves in factorial plots of the raw data.

5.4 THE RESPONSE FUNCTION.

A final implication for the integration function lies in the examination of the response function for the present experiment.

If a case can be made that the response scale used by the subjects, or some stage of the conversion from response formation to the rating produced somehow corrupted the response the subject has formed, it may be said that the data of the present experiment does not reflect failure of the integration procedures, but rather some failure of the rating mechanism to capture the averaging or euclidean nature of the judgements formed.

There are two sources from which such nonlinearity of rating with response could occur. There may have been nonlinearity of responses due to nonlinearity of the scale as used by the subjects, that is, subjects may not have utilised direct 1:1 mapping of judged self-descriptiveness to the visual-analog response medium. This would result in apparrent nonparallelism in both the data plots and the replications method ANOVA.

Birnbaum (1974) found that such apparent departure from the adding or averaging models could be removed through monotonic rescaling of the response scale. Anderson (1982) presents diagrams of four types of factorial plot in which response scale nonlinearity is to be considered. One such diagram (A X B model, page 227, Anderson, 1982) bears similarities to the data of the present experiment - a clustering of responses at either end of the scale spreading out through the central judgements. However, as described earlier (Sect 5.2) it is precisely this feature that may be indicative of an extremity weighting Valuation function, a problem noted by Oden and Anderson (1971). Anderson (1982) also notes that two-factor models typically lack the power for monotone anylsis and that a decision must made as to whether such such analysis clarifies or merely renders the raw data falsly parallel.

Finally concerning the possibility of nonlinearity of the response scale, it must be noted that parallelism, or at least failure of the factorial curves to cross over across levels of the one factor, is an essential feature of that data for which monotone analysis is appropriate.

> For certain models, suitable choice of stimulus levels will yield crossovers that may be used to rule out monotone transformation to additivity. The averaging model...will yield crossovers if the column stimuli are extended to larger values...But although crossovers may disprove an adding model, they do not prove any other model.
>
> (Anderson, 1982, p.229)

The pattern of results of the present experiment, due to crossing over of curves in the factorial plots of the data, therefore contraindicate monotone analysis, as well as providing evidence against an adding model of integration. The crossovers of the present data provide no evidence for consistent nonlinearity of the response scale.

A second possiblity concerning the response function is that the obtained data simply reflect a high degree of arbitrariness to the subjects' responses; that is, some intrinsic weakness of instructions or design such that subjects either did not form judgements at all, or those judgements were not represented in the ratings elicited.

While there is certainly evidence of a high level of noise in the within-subjects data variation, the statistical evidence indicates against the suggestion that error is the greater part of the responses produced. An important feature of the residuals ANOVA design is that the null hypothesis is that all variation from the data is random. Thus there are two circumstances under which nonsignificant results will be obtained. If the data is an exact fit to the model plus or minus error, the residuals ANOVA will yield total nonsignificance. This will also be true, however, if the data is totally or predominantly random. Thus the large number of significant effects in the residuals analysis of variance is itself evidence that the pattern of subjects' responses is significantly nonrandom. Given this, it must be supposed that subjects were generally performing consistently with <u>some</u> form of integration rule, however, the present results give no clear indication as to what that rule may be. The evidence from the present study is thus also inconsistent with any suggestion of gross methodological failure.

5.5 INTEGRATION THEORY AND SELF-RATING: IMPLICATIONS FOR SCHEMA THEORY

The findings of the present experiment falsify several hypotheses concerning integration theory and self-rating. Evidence is provided against a constant-weight averaging model of integration, and a euclidean model of the same function, and thus also against the geometric representations of these models discussed in Chapter 2. While there is some indication of an averaging-type integration mode with extremity weighting (Sect 5.2), that evidence is only secondary and in part contraindicated by the extent to which curves in the factorial plots of that data obtained cross over, a finding not entirely inconsistent but nor supportive of this model. Nonlinearity of the response scale, rectifiable by monotonic rescaling, while a possibility, is firstly beyond the power of the two-factor design utilised herein, and secondly could not remove the crossover observed in the factorial data.

Accordingly, the present experiment reveals little concerning the merit of regarding schemata as analogous with points in N-Dimensional space. Certainly the two-dimensional analogy used in the present experiment appears not to capture the principles by which schematic self-rating is carried out.

Simultaneous estimation of position and weight- the major potential contribution of Integration Theory (Anderson, 1981, 1983) to the understanding of self schemata is , however, no less valuable for the failure of the present experiment. The results obtained herein suggest not that the estimation of position and weight as separate and independent aspects of a single schema is invalid or impossible, but rather that a more complex and adequate model of information integration is required before such essential estimation can take place.

APPENDIX I. PILOT WORK FOR THE PRESENT STUDY

There were two piloting processes prior to the major experimentation , the first concerning the properties and ordering of the qualifiers, the second more directly assessing the use of visual-analog scale as a response medium.

1 QUALIFIER SELECTION. A pool of eleven qualifiers was originally chosen for item analysis. These were: "Extremely", "Very", "Rather", "Quite", "Fairly", "Reasonably", "Somewhat", "Moderately", "Slightly", "A Little" and "Minimally". Twenty subjects were asked to rank order these items from that which made a thing described the "Biggest or most" to that which made a thing the "Smallest or least". The means and standard deviations of ranked positions were than calculated, the results being as follows:

Qualifier	Mean Ranking	S.D.
Extremely	11.00	0.000
Very	10.00	0.000
Rather	8.40	0.516
Quite	7.00	2.108
Fairly	6.00	1.333
Reasonably	6.20	0.789
Somewhat	5.20	1.317
Moderately	6.00	2.211
Slightly	3.00	0.816
A Little	2.20	0.422
Minimally	1.00	0.000

The criteria for inclusion into the experimental items were i. Qualifiers that were spread across the full length of the magnitude dimension, and ii. preference was given for items with low standard deviations. "Extremely" and "Minimally" were thus immediately included. "Very" was rejected on the distribution criterion, in spite of its low S.D. "Rather" and "Reasonably" were included as the midrange qualifiers due to their being more consistently ranked than "Quite", "Fairly", "Somewhat" or "Moderately" - the alternative midrange items. "Slightly" was chosen in preference to "A Little" on the distribution criterion- it represented a point midway between "Reasonably" and "Minimally". The unqualified condition was not investigated in this analysis.

The Qualifers "Very", "Moderately" and "A Little" were used in the practice trials.

2. RESPONSE MEDIUM.

The utility of the visual analog scale was investigated in a separate pilot study using a diiferent sample from that described above. It was felt that such a device, being without any numerical scale, would remove interval scaling on the part of the subjects, as well as emphasising the continuity of possibile judgements.

A person likeability task (Anderson, 1965, 1981) was utlised in which subjects were asked to mark on a line a cross representing how much they believed they would like the person described. The left-hand end of the line was marked "very little", the right-hand end "a lot". The qualifiers "Minimally", "Slightly", "Reasonably", "Rather", and "Extremely" were used, as well as an unqualified condition. These were combined with the adjectives "Calm" and "Excitable" and ""Happy" and "Unhappy", with one of the former always as the first and one of the latter always as the second adjective. The items were generated thus were arranged randomly in a booklet that was then administered to 20 subjects, together with the instructions.

Parallelism was observed in the factorial plots for all subjects, although there was a high level of error. These results are consistent with those of Anderson (1965, 1981), and were taken as evidence that the use of the visual-analog scale preserved parallelism in judgement, as well as demonstrating that the use of qualifiers served to locate items along the dimension qualified in the manner described in Chapter Two.

Plots of the rated likeability of each adjective coupled with each qualifier condition demonstrated the "linear fan" pattern representative of multiplicative combination of items (Anderson, 1981), illustating that the adjectives did indeed act as multiplicative constants for the adjectives - the qualifed adjective thus defining a point somwhere between a zero and an infinite value for that qualifier.

APPENDIX II. PRELIMINARY MODEL FITTING FOR PARAMETER ESTIMATION.

AVERAGING MODEL.

1. ABSTRACT (DEPENDENT/CALM) ADJECTIVE TYPE.

		Estimated Parameter Values								
SU#	O-E_2.	MIN.	SLI.	REA.	RAT.	UNQ.	EXT.	C_A	C_B	W_A
01	0.07	0.00	0.00	0.00	1.00	1.00	1.00	0.46	0.54	0.41
02	1.07	0.00	0.00	0.32	1.00	1.00	1.00	0.72	0.60	0.44
03	0.48	0.00	0.01	0.18	1.00	1.00	1.00	0.58	0.00	0.89
04	0.48	0.00	0.00	0.00	1.00	1.00	1.00	0.69	0.50	0.59
05	1.64	0.00	0.00	0.00	1.00	1.00	1.00	0.21	0.39	0.46
06	0.92	0.00	0.27	0.50	0.87	0.99	1.00	0.78	0.01	0.71
07	0.48	0.00	0.44	0.50	1.00	1.00	1.00	0.77	0.87	0.91
08	0.98	0.00	0.00	0.00	1.00	1.00	1.00	0.54	0.35	0.51
09	0.55	0.00	0.00	0.00	1.00	1.00	1.00	0.40	0.46	0.49
10	0.72	0.00	0.31	0.45	0.98	0.93	1.00	0.69	0.67	0.86
11	0.60	0.00	0.01	0.55	1.00	1.00	1.00	0.48	0.05	0.58
12	1.34	0.00	0.23	0.20	1.00	1.00	1.00	0.66	0.92	0.93
13	0.70	0.00	0.00	0.00	1.00	1.00	1.00	0.66	0.39	0.44
14	0.63	0.00	0.21	0.54	0.94	0.96	1.00	0.76	0.72	0.56
15	0.75	0.00	0.25	0.68	1.00	0.95	1.00	0.79	0.00	0.70
16	0.60	0.00	0.35	0.48	0.95	0.89	1.00	0.79	0.35	0.79
17	0.52	0.00	0.60	0.80	0.76	0.79	1.00	0.57	0.87	0.14
18	1.13	0.00	0.00	0.00	1.00	1.00	1.00	0.59	0.31	0.51

SU#	O-E$_2$.	MIN.	SLI.	REA.	RAT.	UNQ.	EXT.	C_A	C_B	W_A
19	1.13	0.00	0.12	0.67	0.97	0.81	1.00	0.87	0.19	0.78
20	2.08	0.00	0.00	0.00	1.00	1.00	1.00	0.49	0.38	0.69
21	4.21	0.00	0.06	0.00	1.00	0.60	1.00	0.59	0.19	0.59
22	0.95	0.00	0.26	0.58	1.00	0.92	1.00	0.79	0.34	0.68
23	1.07	0.00	0.27	0.71	0.94	0.64	1.00	0.77	0.35	0.55
24	0.65	0.00	0.05	0.22	0.74	0.84	1.00	0.40	0.60	0.43
25	1.00	0.00	0.28	0.00	0.92	0.86	1.00	0.36	0.42	0.46
26	0.72	0.00	0.28	0.46	0.76	1.00	1.00	0.48	0.20	0.57
27	1.13	0.00	0.00	0.25	1.00	1.00	1.00	0.64	0.00	0.85

S# = Subject Number, O-E2 = Function Value (summed squared Observed-Expected Difference), MIN. = Minimally, SLI. = Slightly, REA. = Reasonably, RAT. = Rather, UNQ. = Unqualified, EXT. = Extremely, C_A = Comparitor point upon dimension A, C_B = Comparitor point upon Dimension B, W_A = Weight of Dimension A. Weight of dimension B (W_B) = 1 - W_A. Underscored values are those for which the iteration procedure reported no convergence with the model in 500 iterations

2. CONCRETE (TALL/FAIR) ADJECTIVE TYPE.

		Estimated Parameter Values								
SU#	O-E_2.	MIN.	SLI.	REA.	RAT.	UNQ.	EXT.	C_A	C_B	W_A
01	0.43	0.00	0.10	0.16	1.00	0.84	1.00	0.55	1.00	0.93
02	0.62	0.00	0.88	0.47	1.00	1.00	1.00	0.75	0.00	0.91
03	0.39	0.00	0.00	0.23	0.90	1.00	1.00	0.55	0.45	1.00
04	0.38	0.00	0.15	0.27	0.85	0.80	1.00	0.57	0.52	0.70
05	1.64	0.00	0.00	0.00	1.00	1.00	1.00	0.21	0.39	0.46
06	1.43	0.00	0.00	0.00	1.00	1.00	1.00	0.21	0.56	0.51
07	1.21	0.00	0.00	0.00	1.00	1.00	1.00	0.45	0.49	0.23
08	1.30	0.00	0.16	0.36	0.94	0.86	1.00	0.57	0.18	0.79
09	0.87	0.00	0.02	0.17	1.00	1.00	1.00	0.60	0.42	1.00
10	0.46	0.00	0.47	0.43	0.80	0.57	1.00	0.68	0.61	0.47
11	0.51	0.00	0.52	0.58	0.84	1.00	1.00	0.72	0.65	0.43
12	1.17	0.00	0.30	0.36	0.90	0.44	1.00	0.69	0.43	0.67
13	0.77	0.00	0.36	0.49	1.00	0.79	1.00	0.69	0.68	0.55
14	1.83	0.00	0.00	0.00	1.00	1.00	1.00	0.34	0.54	0.41
15	0.16	0.00	0.21	0.34	0.85	1.00	1.00	0.36	0.48	0.79
16	0.41	0.00	0.44	0.57	0.93	0.69	1.00	0.78	0.47	0.80
17	1.68	0.00	0.33	0.59	0.80	0.62	1.00	0.62	0.63	0.40
18	0.81	0.00	0.25	0.51	1.00	0.83	1.00	0.58	0.72	0.22
19	1.05	0.00	0.53	0.76	0.95	0.73	1.00	0.80	0.78	0.60
20	1.18	0.00	0.02	0.58	1.00	0.82	1.00	0.75	0.67	0.51

SU#	O-E_2.	MIN.	SLI.	REA.	RAT.	UNQ.	EXT.	C_A	C_B	W_A
21	2.78	0.00	0.61	0.44	0.60	1.00	1.00	0.61	0.67	0.40
22	1.78	0.00	0.00	0.00	1.00	1.00	1.00	0.35	0.54	0.51
23	2.02	0.00	0.24	0.00	0.81	0.76	1.00	1.00	0.32	0.18
24	0.79	0.00	0.35	0.61	0.60	0.73	1.00	0.67	0.69	0.58
25	~~1.04~~	0.00	0.51	0.74	0.72	0.80	1.00	0.80	0.74	0.51
26	1.01	0.00	0.50	0.73	0.76	0.82	1.00	0.82	0.77	0.60
27	0.79	0.00	0.41	0.76	0.77	0.78	1.00	0.77	0.70	0.50

S# = Subject Number, O-E2 = Function Value (summed squared Observed-Expected Difference), MIN. = Minimally, SLI. = Slightly, REA. = Reasonably, RAT. = Rather, UNQ. = Unqualified, EXT. = Extremely, C_A = Comparitor point upon dimension A, C_B = Comparitor point upon Dimension B, W_A = Weight of Dimension A. Weight of dimension B (W_B) = 1 - W_A. Underscored values are thos for which the iteration procedure reported no convergence with the model in 500 iterations.

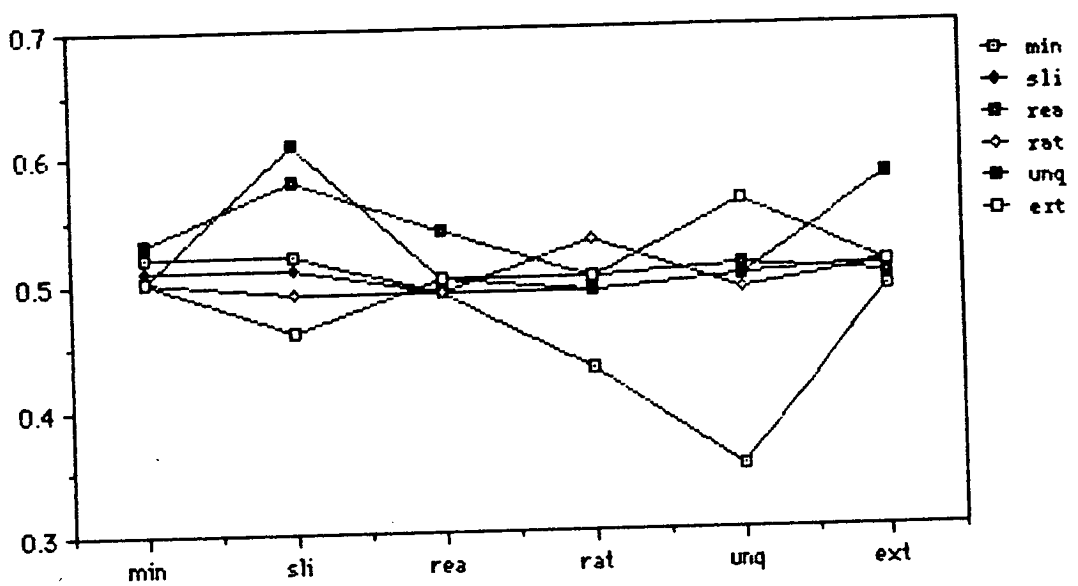
APPENDIX III: FACTORIAL REPRESENTATION OF RAW DATA

This appendix consists of factorial plots of the responses elicited from all subjects for each of Abstract and Concrete Adjective Types. Responses have been scaled to between 0 and 100 to maintain consistency with the data used in analysis.

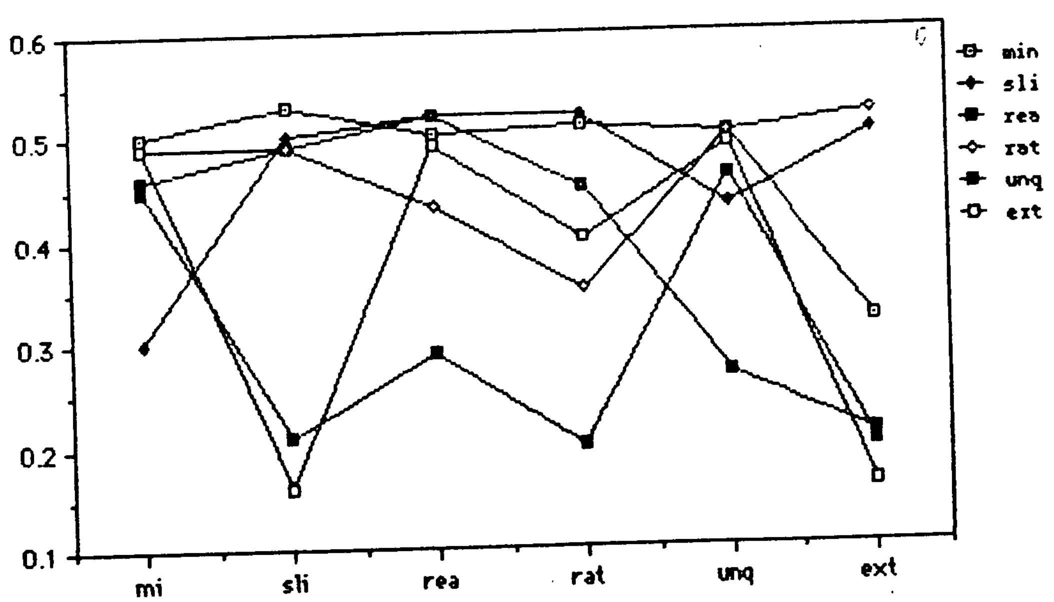
Each plot also lists the Instructional Set condition to which the subject was allocated: "Global" being Global Instructional Set, "Atomic", the Atomic Instructional Set, and "Atomic. neg." the Atomic, Negative Set.

Plotting the data in this way is the preferred representational technique of Anderson (1982) as it enables ready observation of the extent of parallelism in the raw data, thus providing a better indication of the goodness of fit of the averaging model than would a staightforward list of ratings. Were the fit to the averaging model exact, the observed values would describe curves which would be parallel plus or minus error. The greater the degree of crossover of the curves, the poorer the fit of the averaging model to the data.

The euclidean model also predicts that curves in a factorial plot of responses will not cross, but that they will converge asymptotically toward the extreme ends of the horizontal axis.



Subject 1, Global, Abstract



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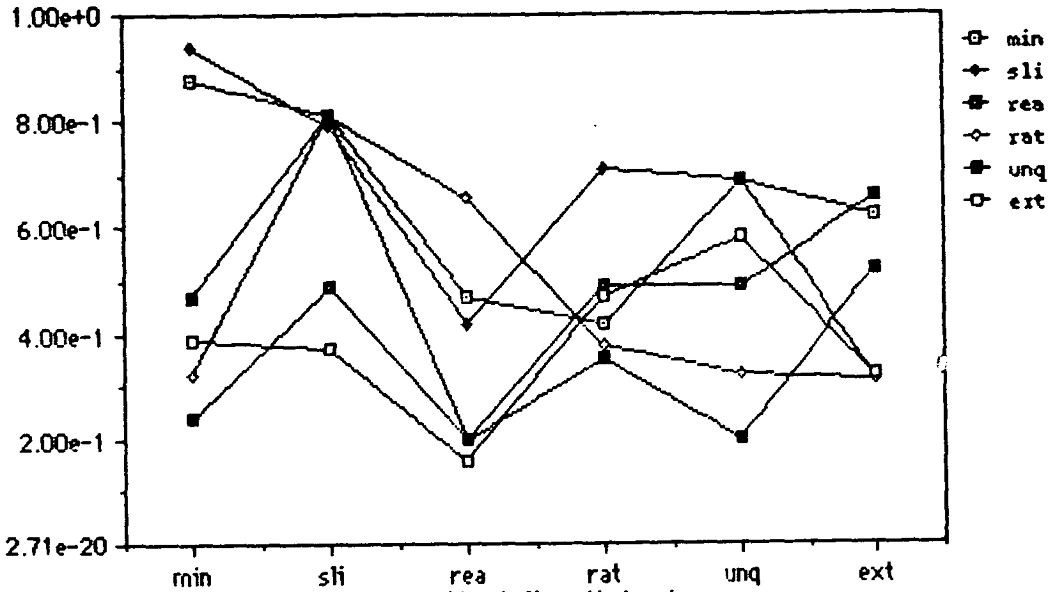

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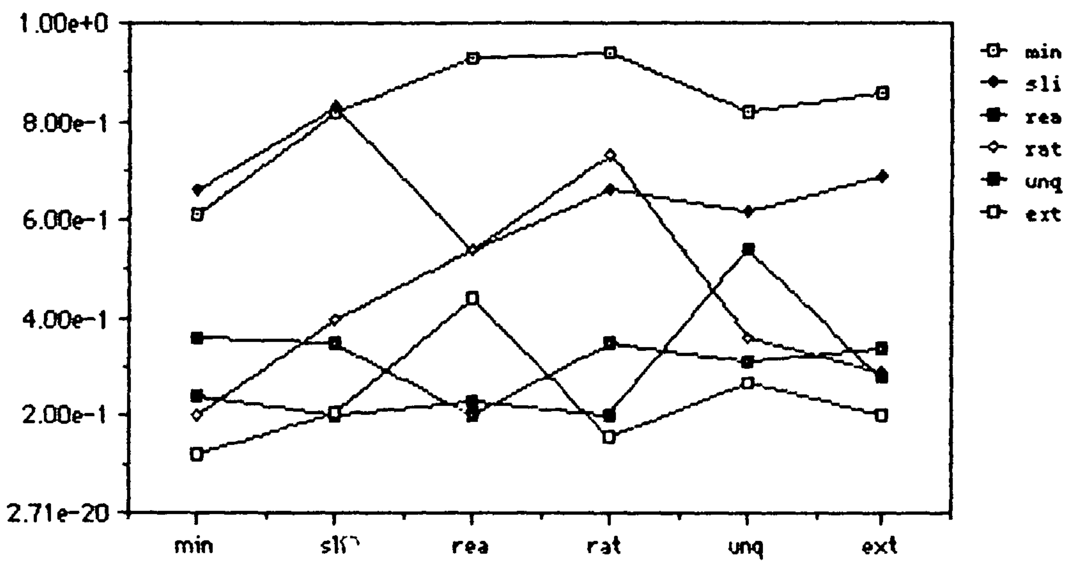

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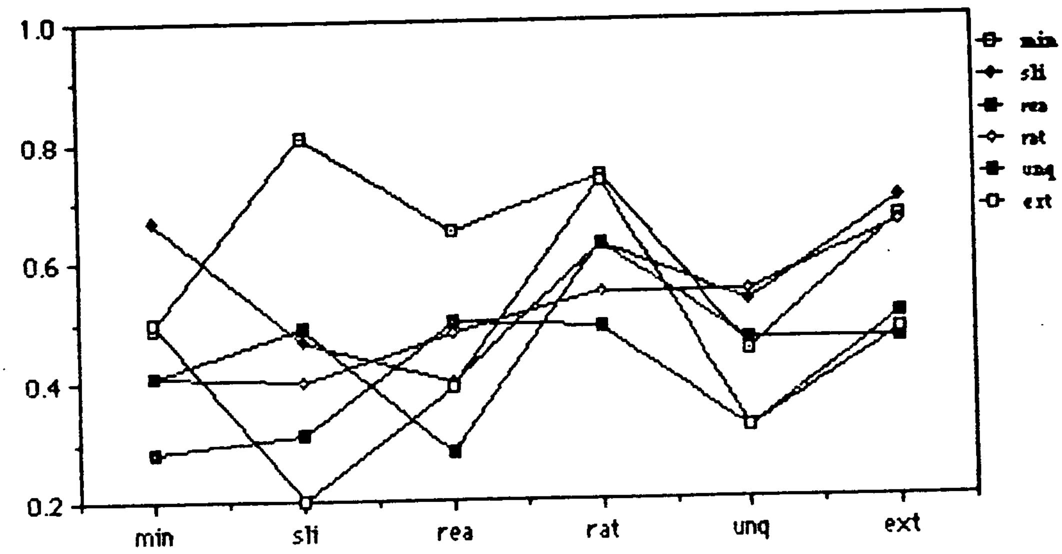

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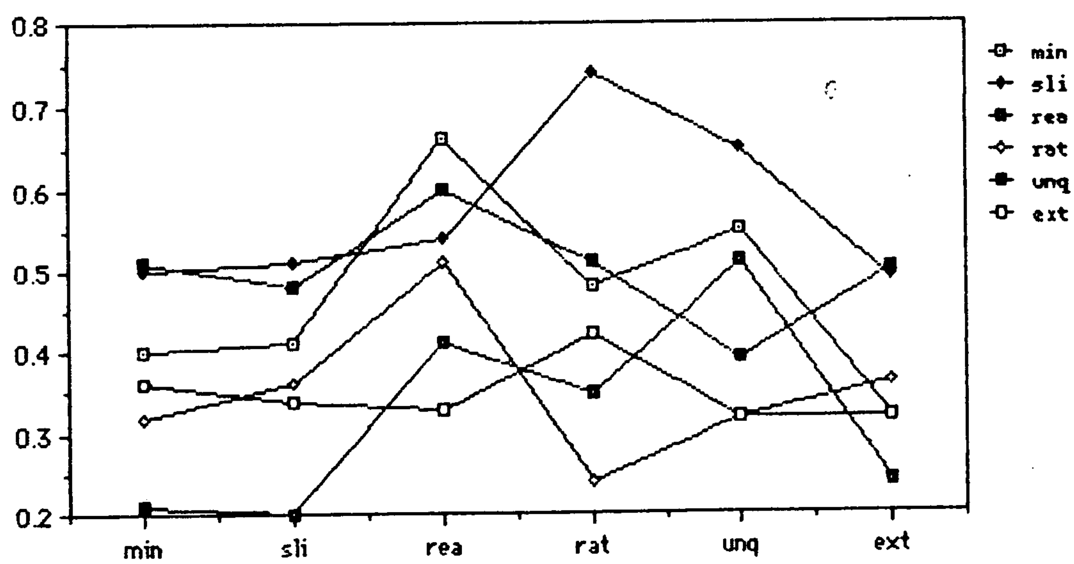

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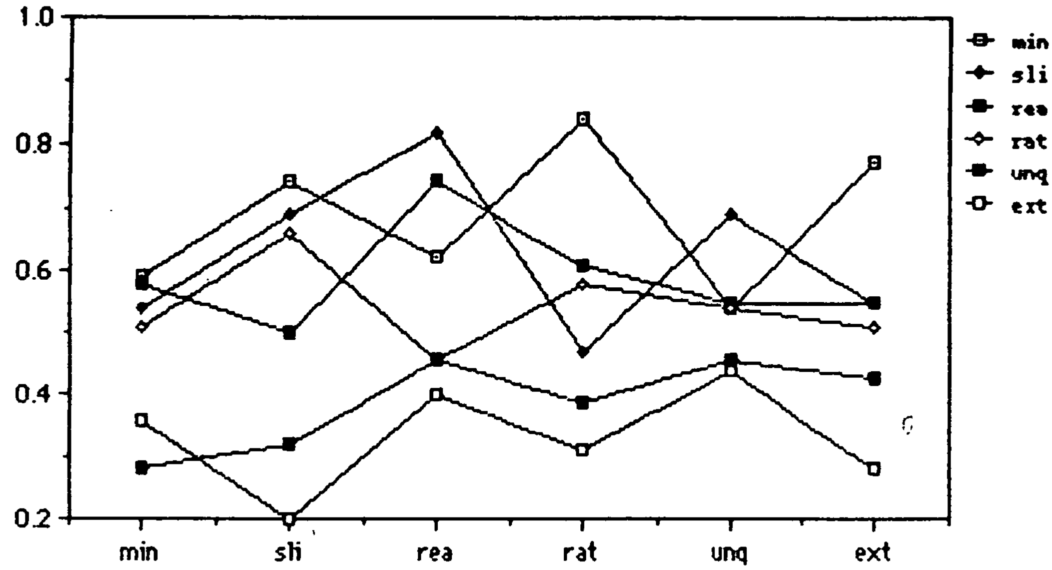
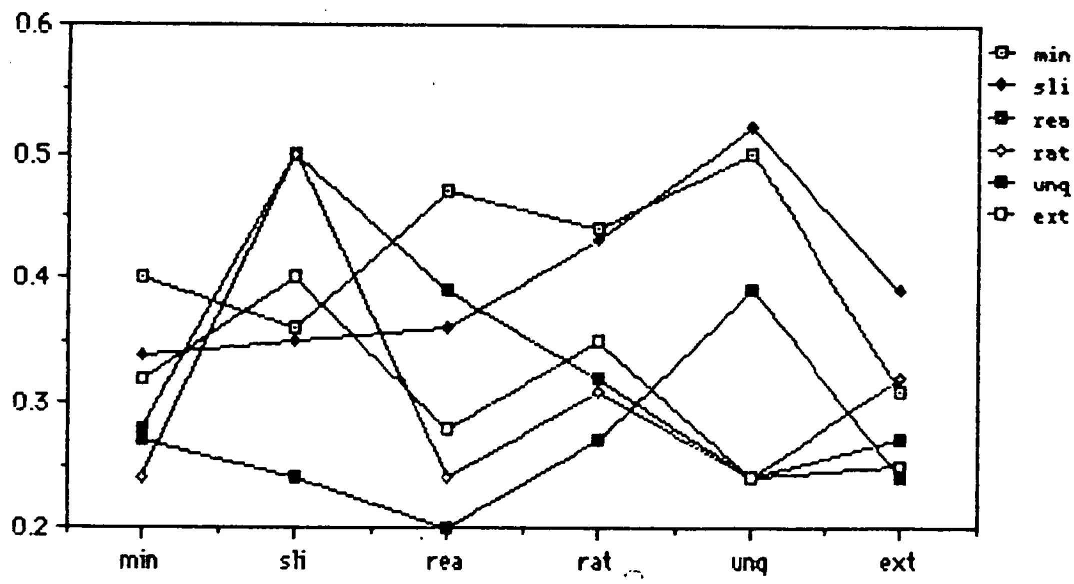
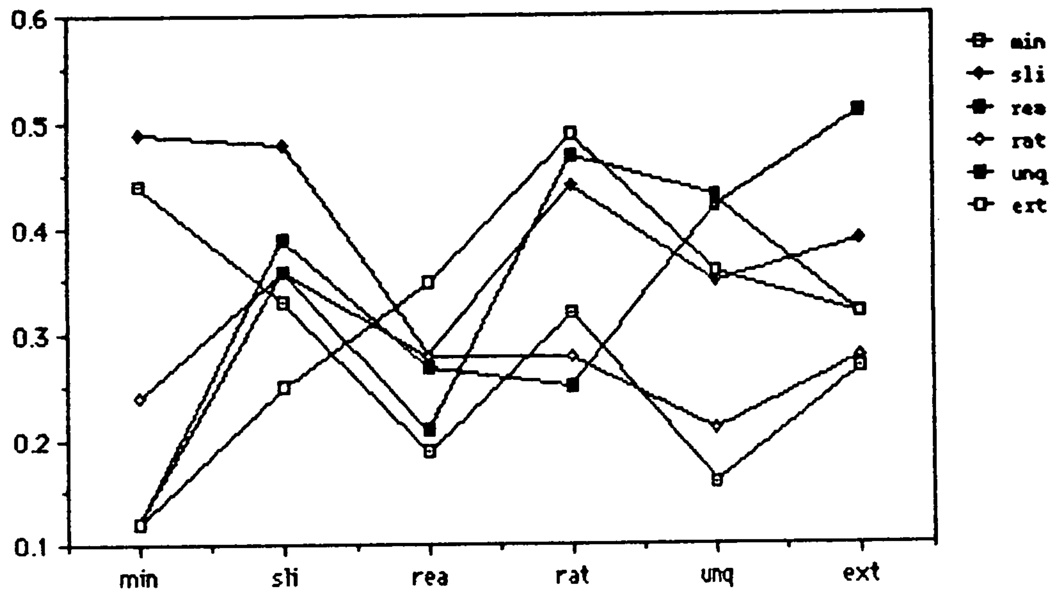


Subject 4, Global, Abstract

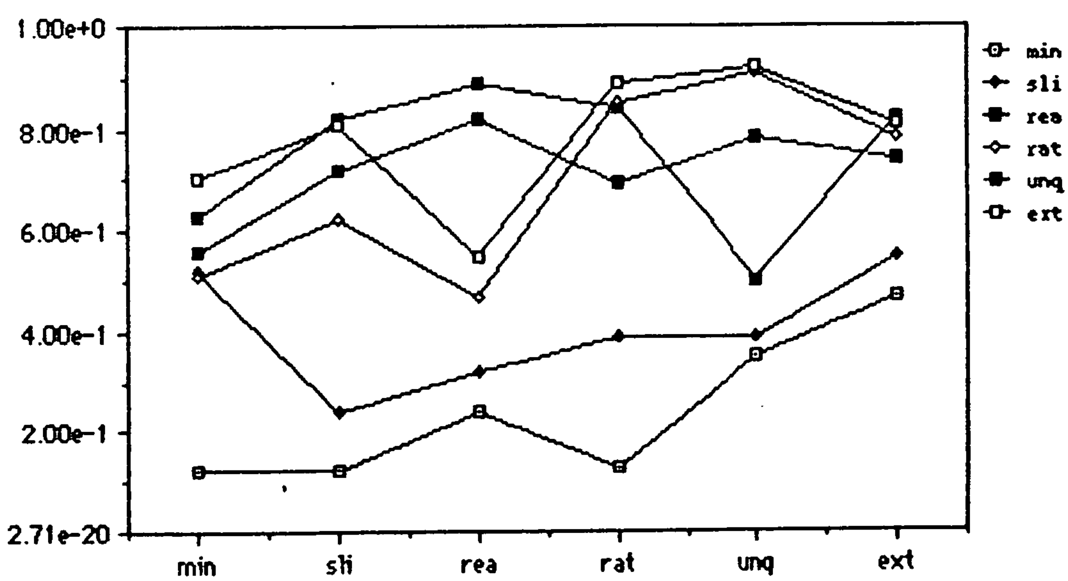


Subject 4, Global, Concrete

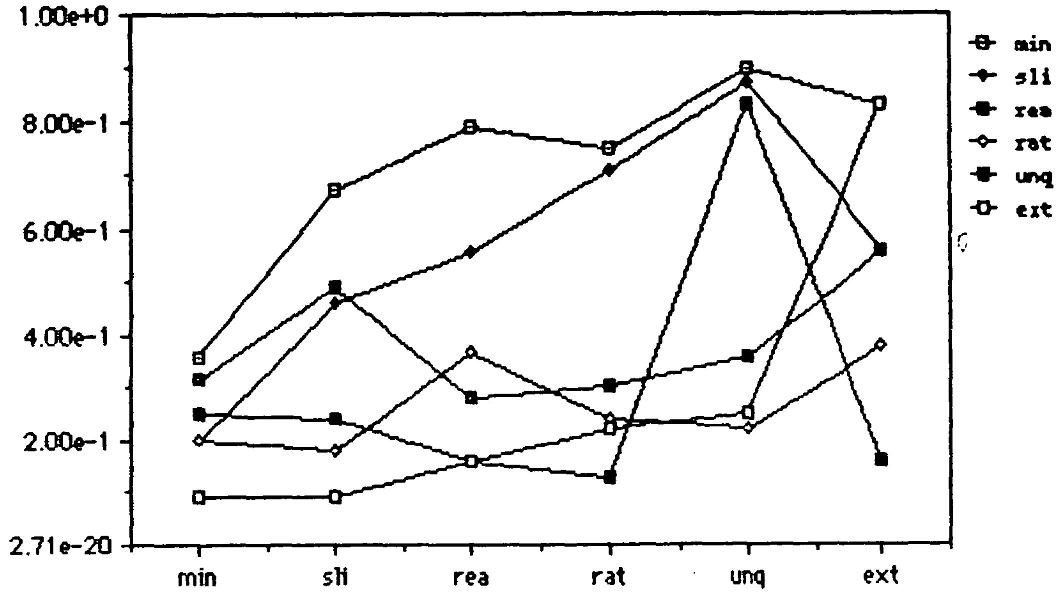
p2



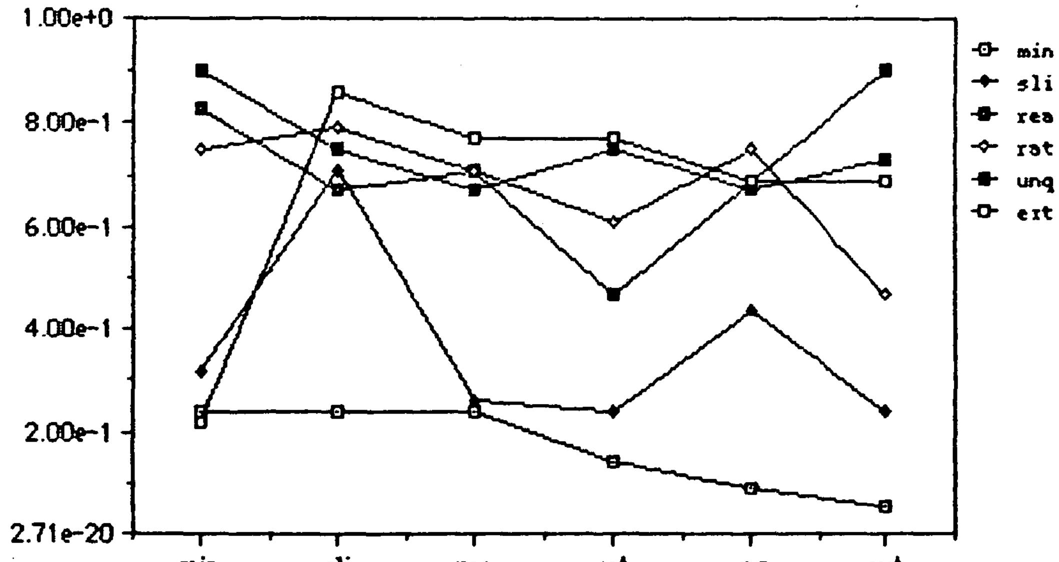
Subject 5, Atomic neg. Abstract



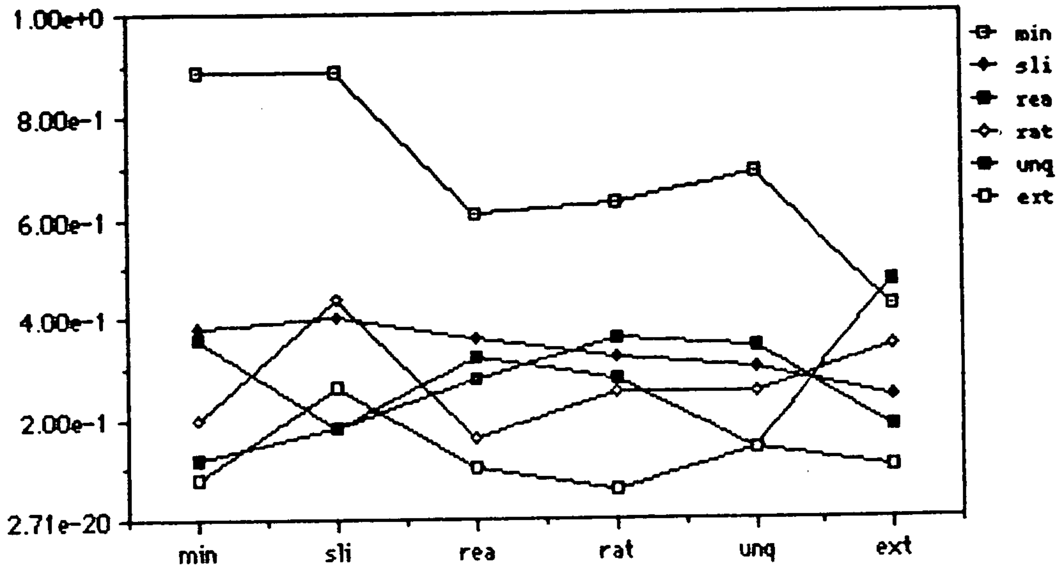
Subject 5, Atomic neg. Concrete



Subject 6, Atomic Abstract



Subject 6, Atomic, Concrete



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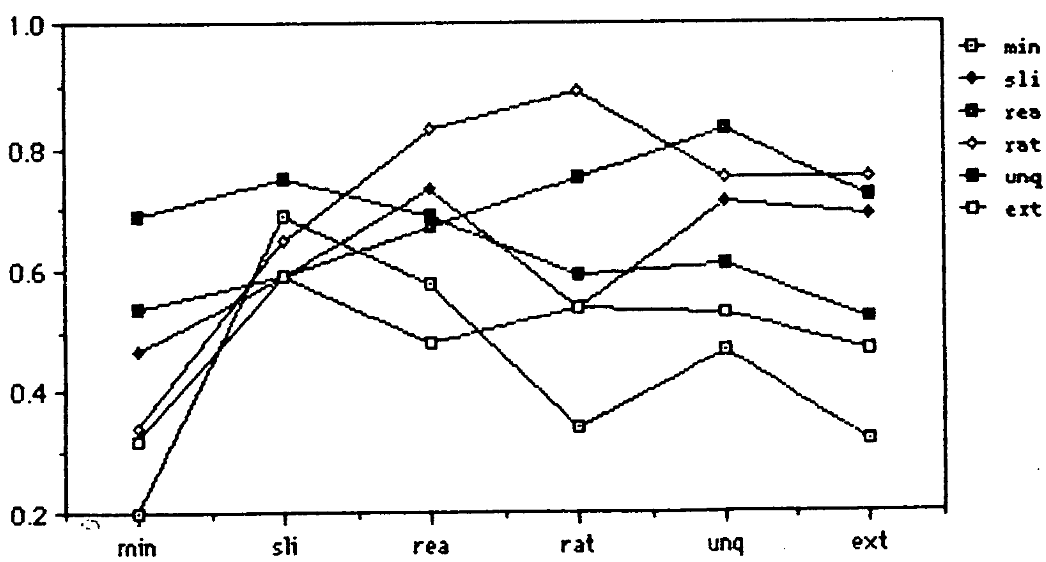

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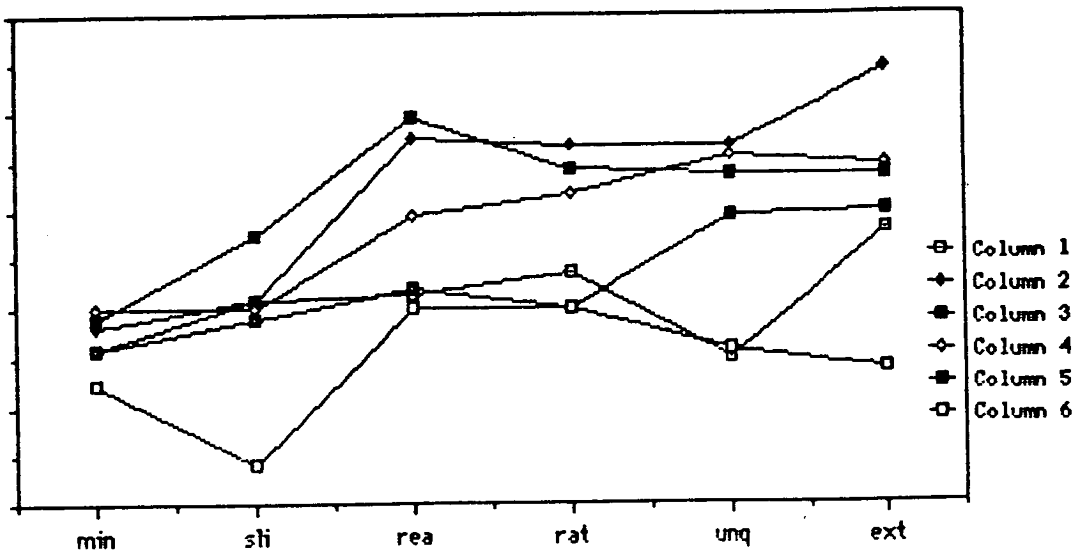

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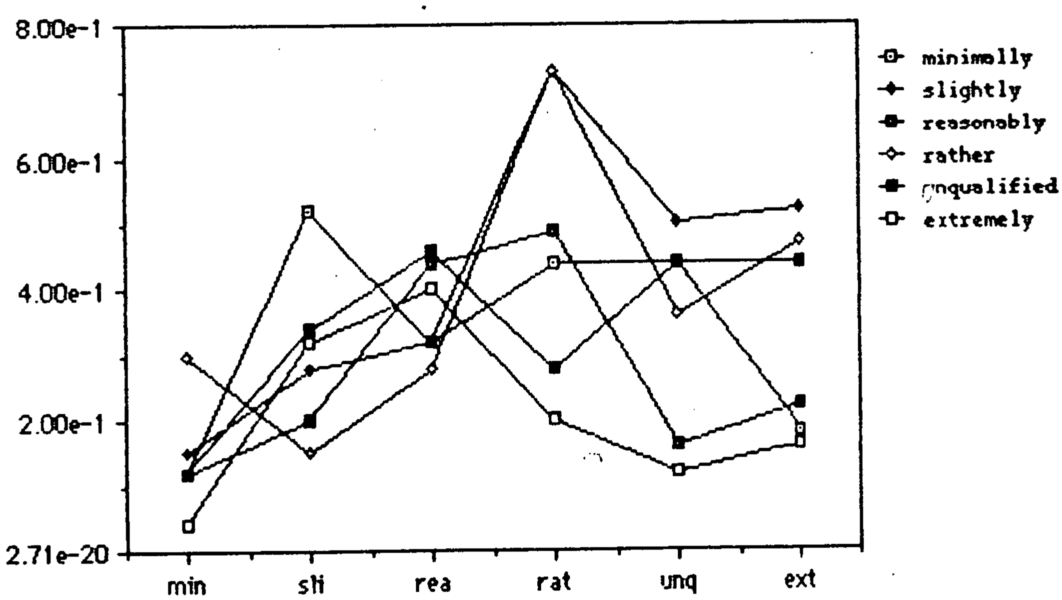

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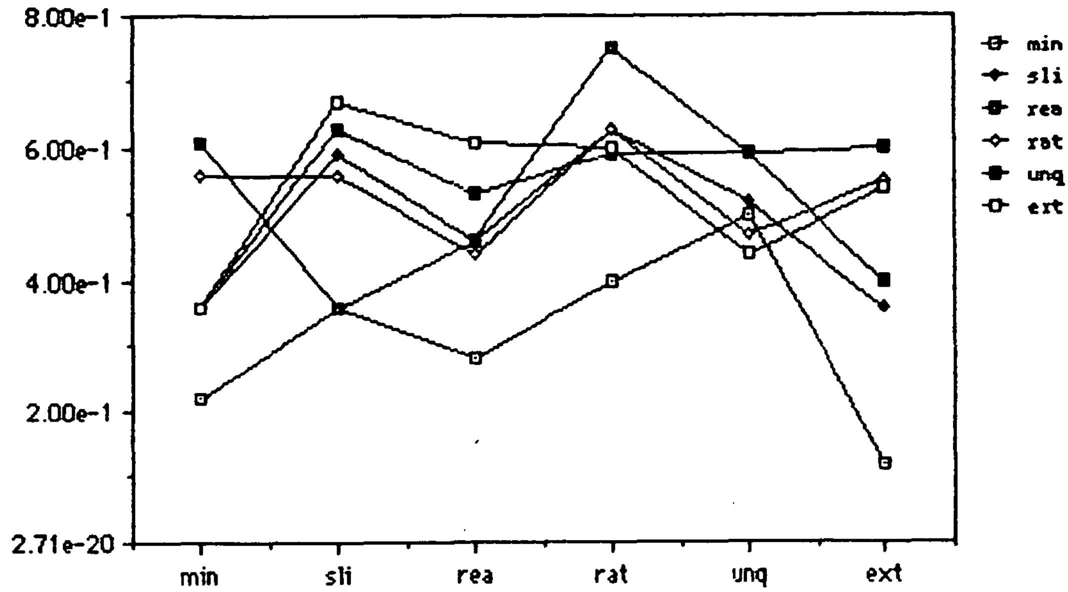

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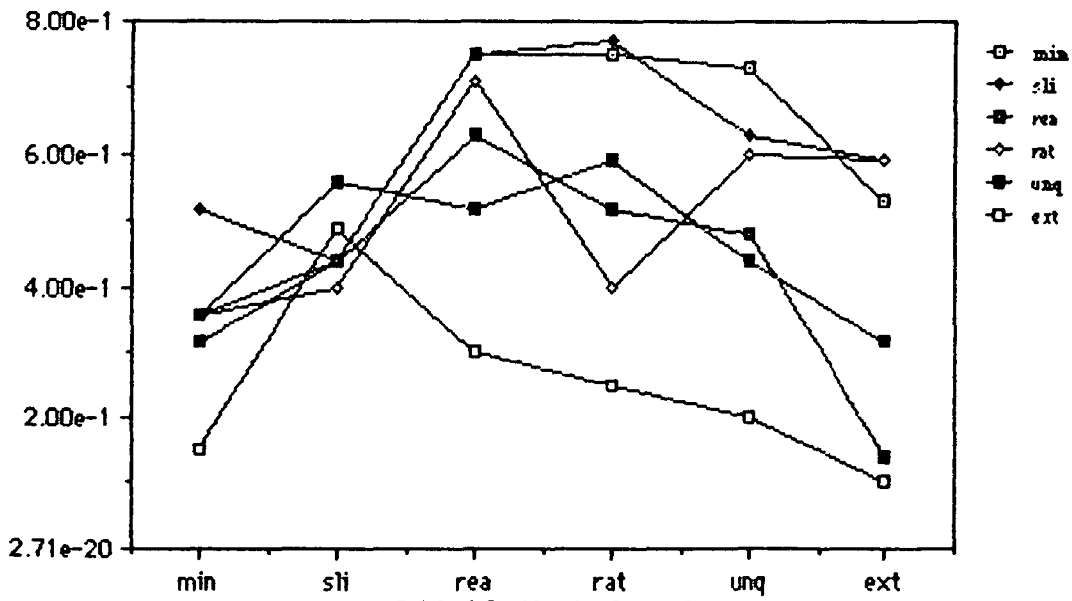

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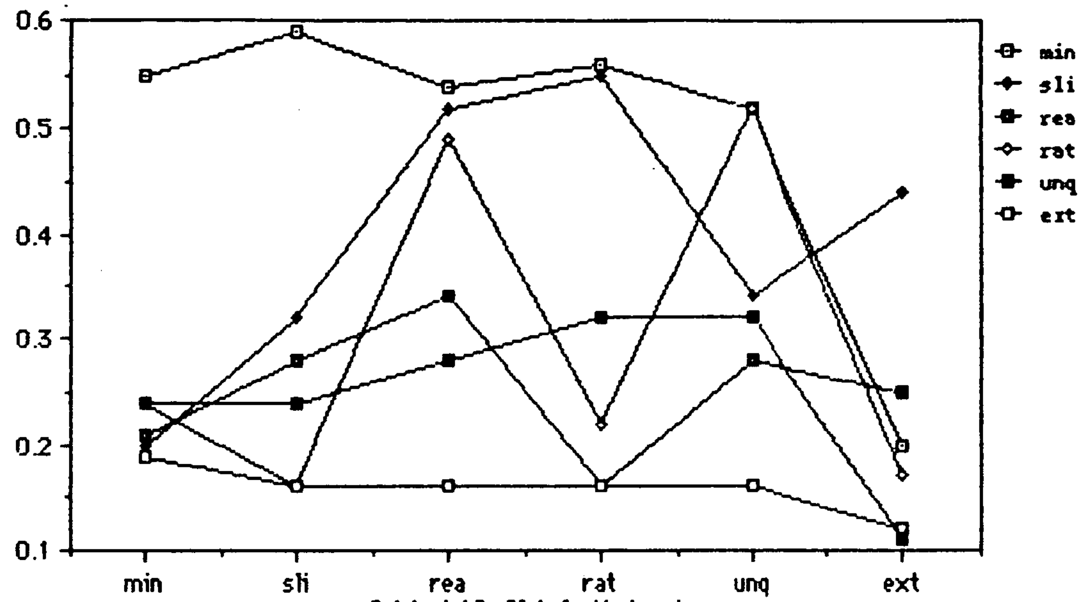

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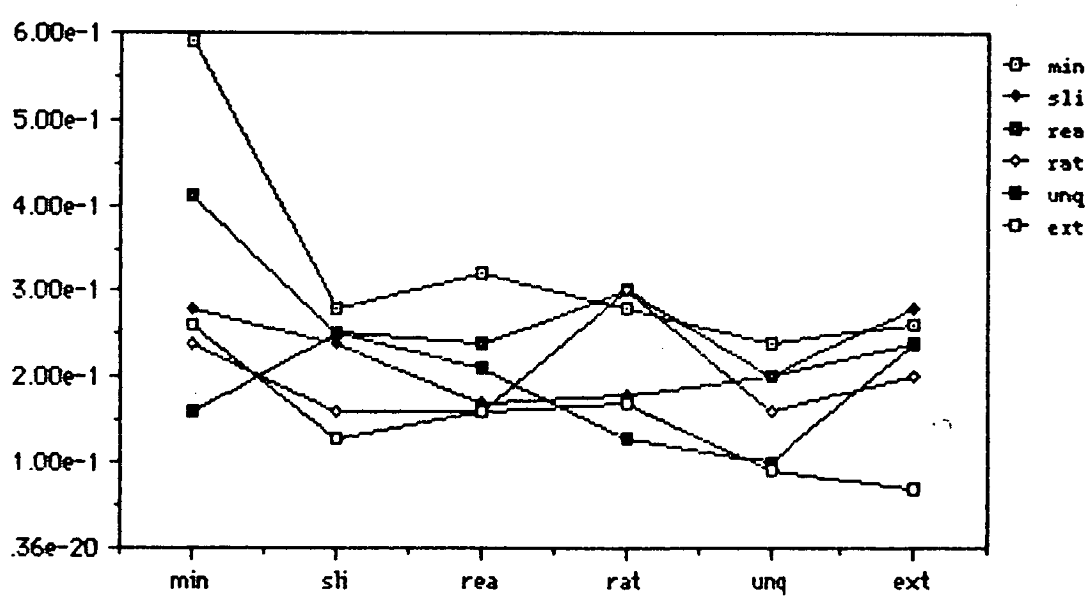

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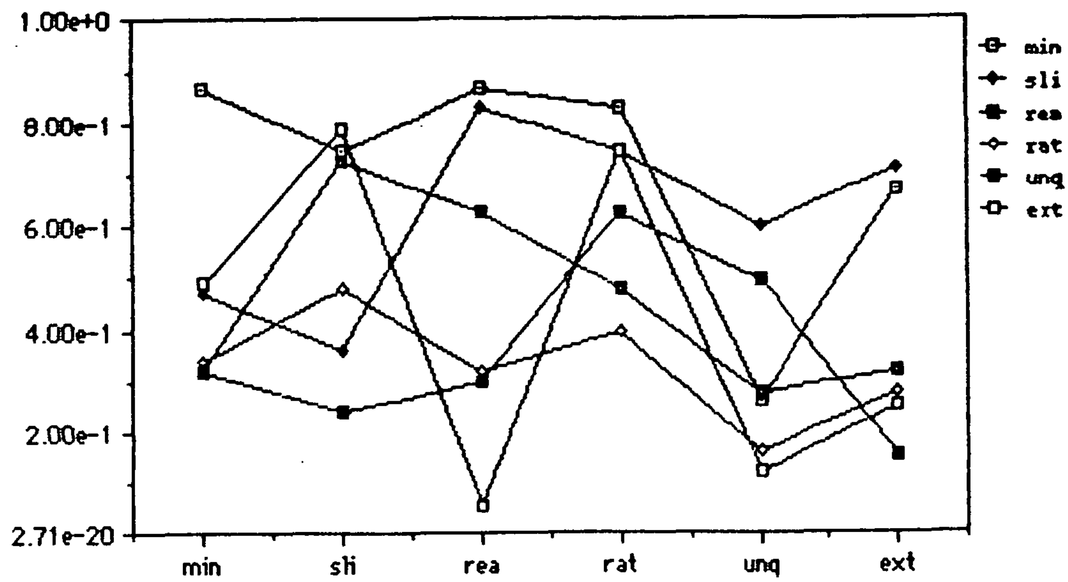

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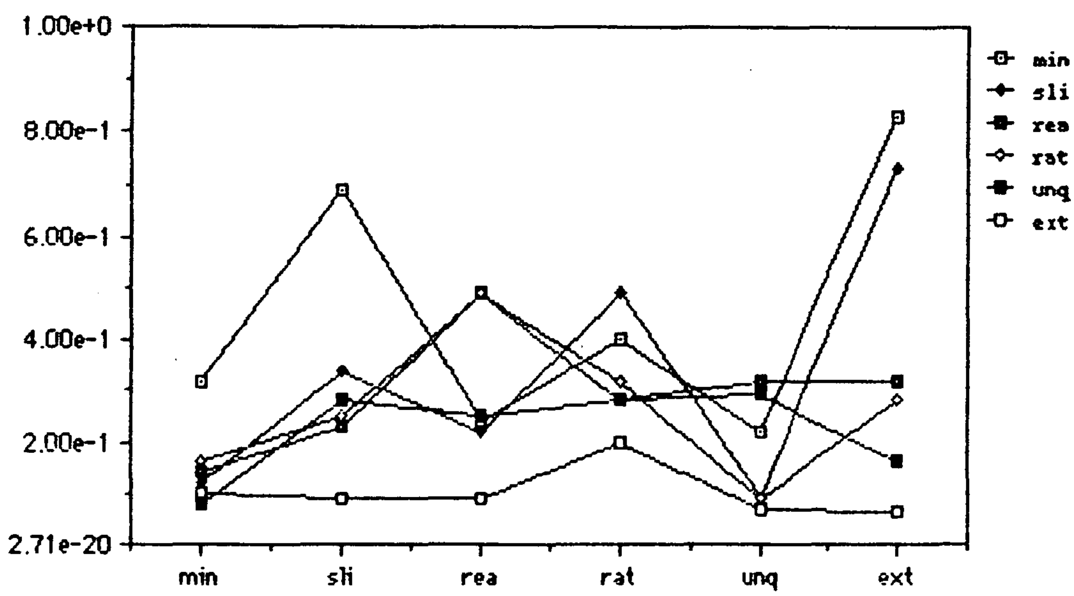

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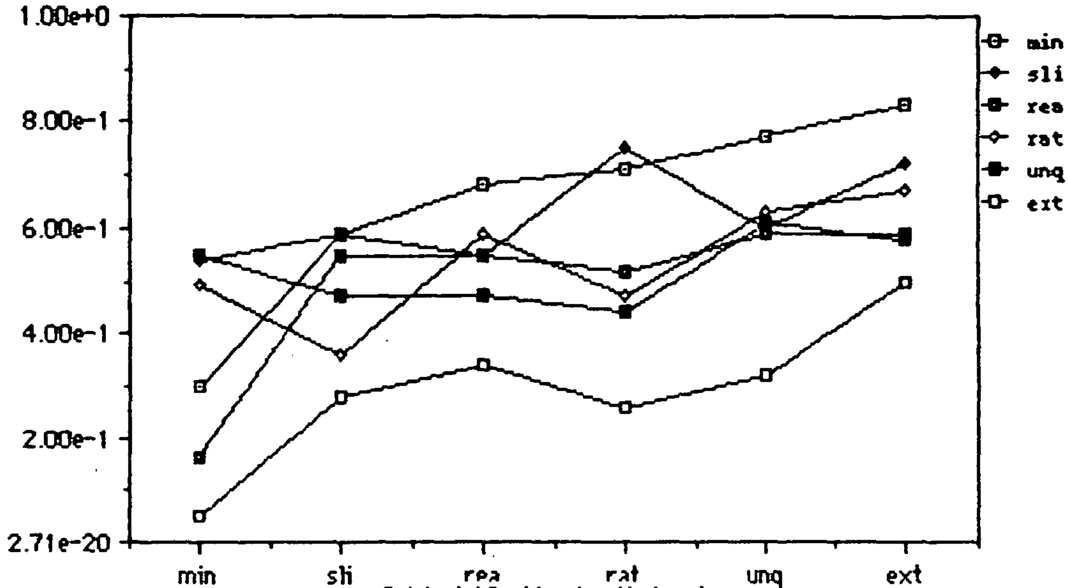

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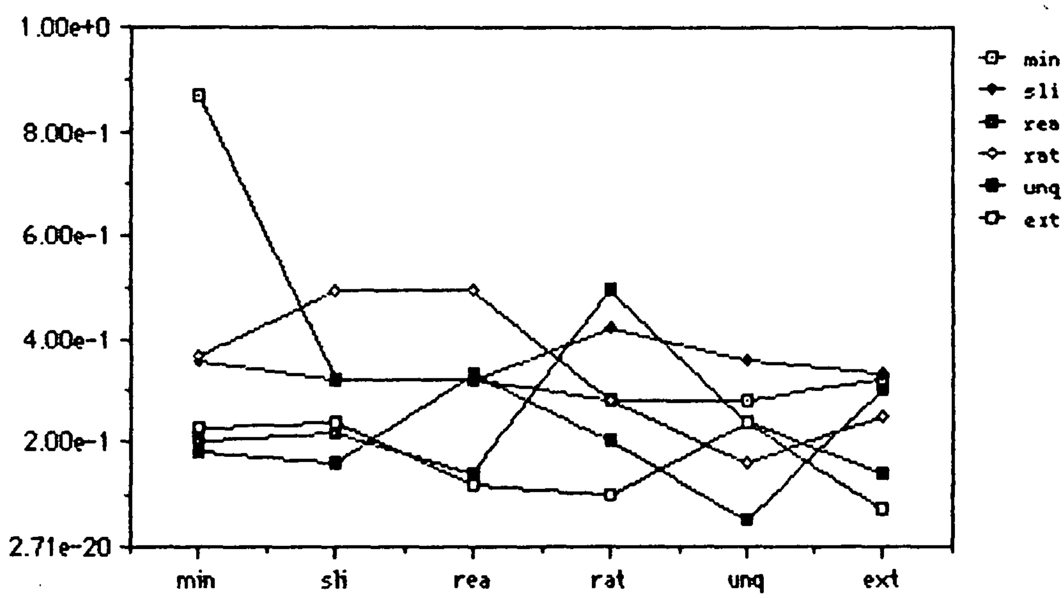

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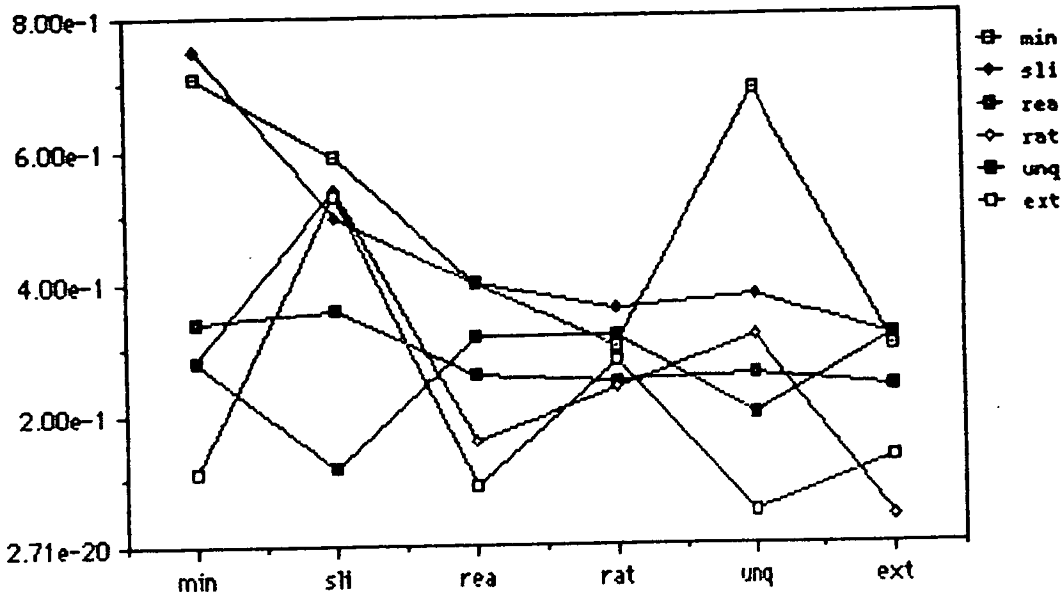

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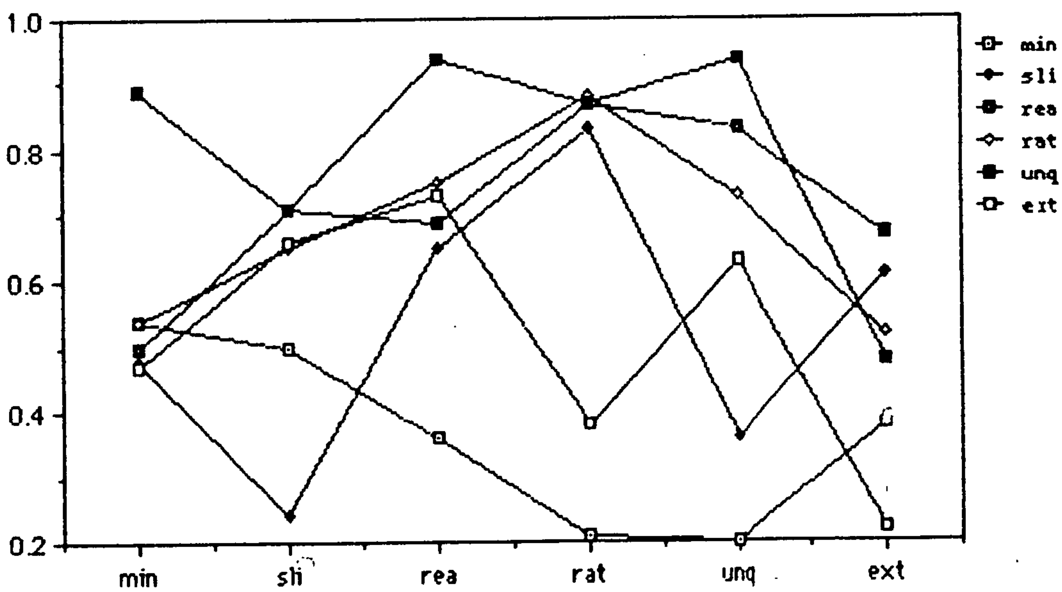

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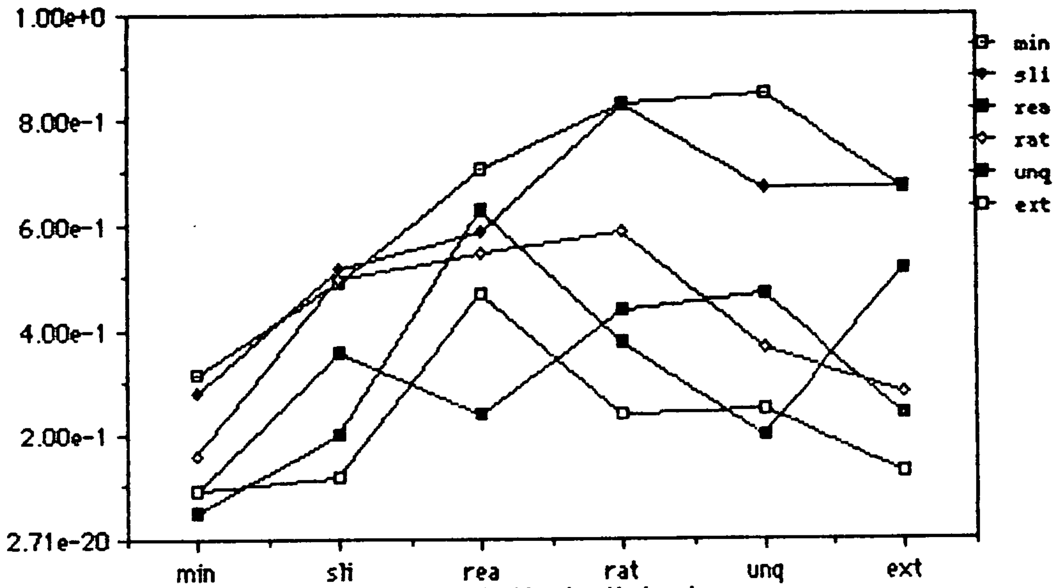

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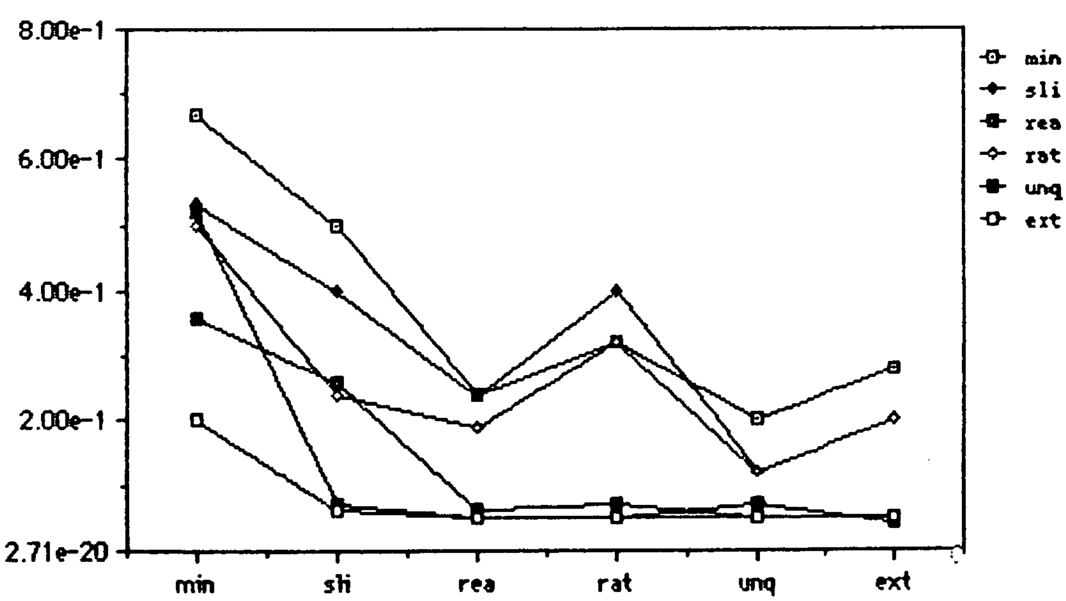

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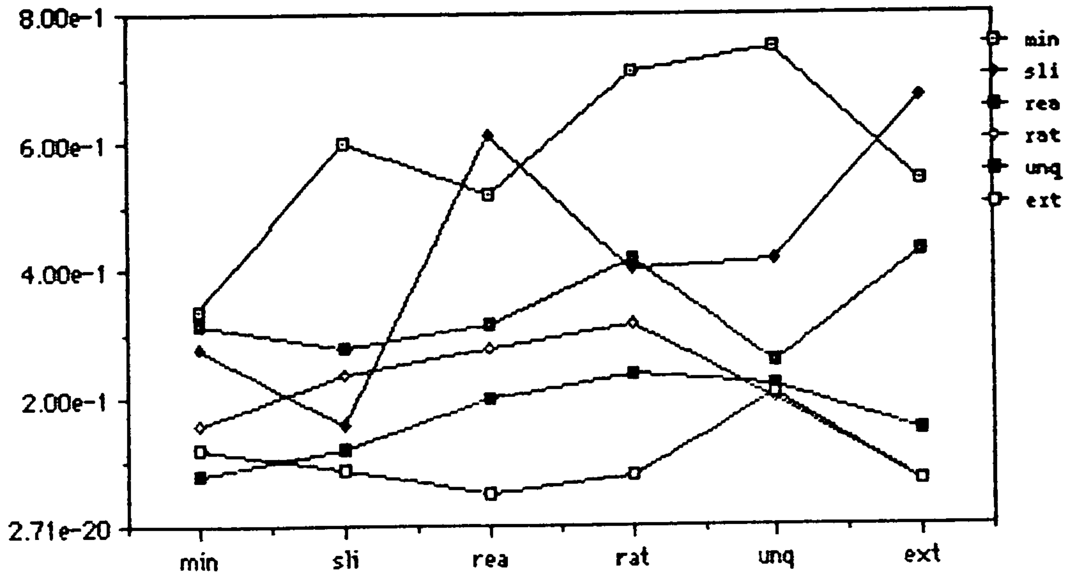

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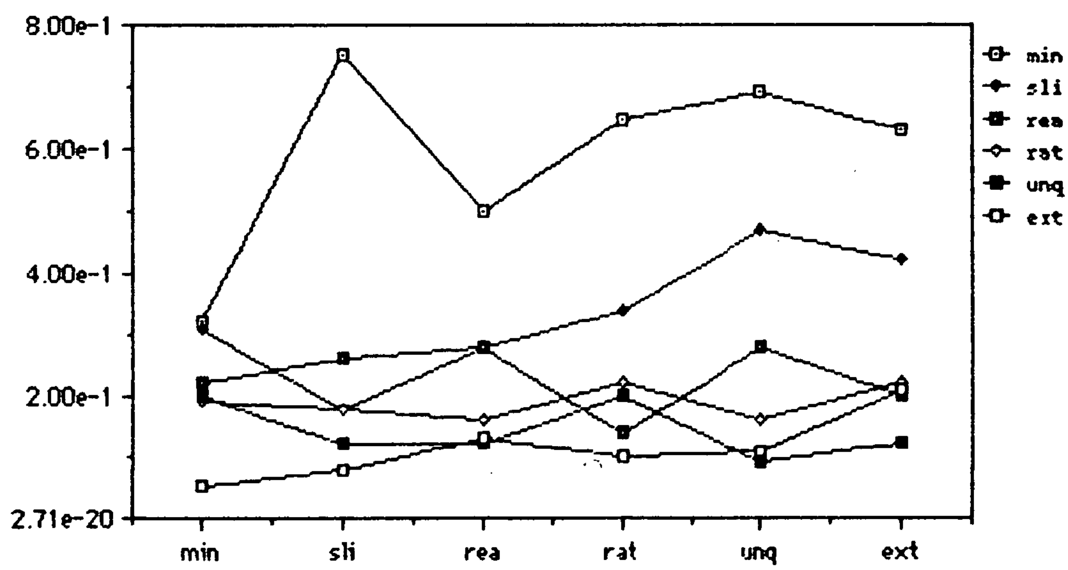

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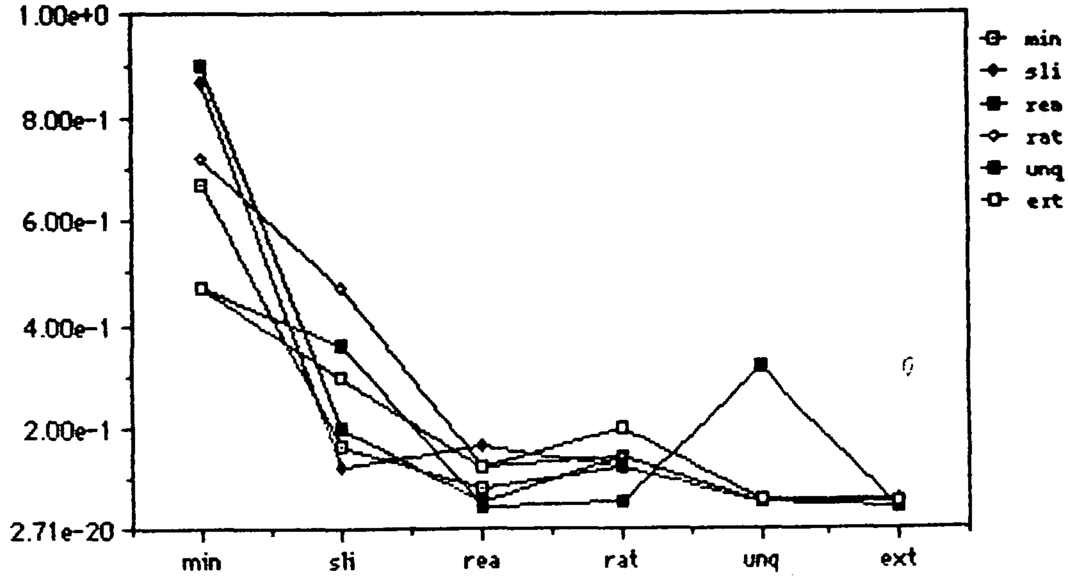

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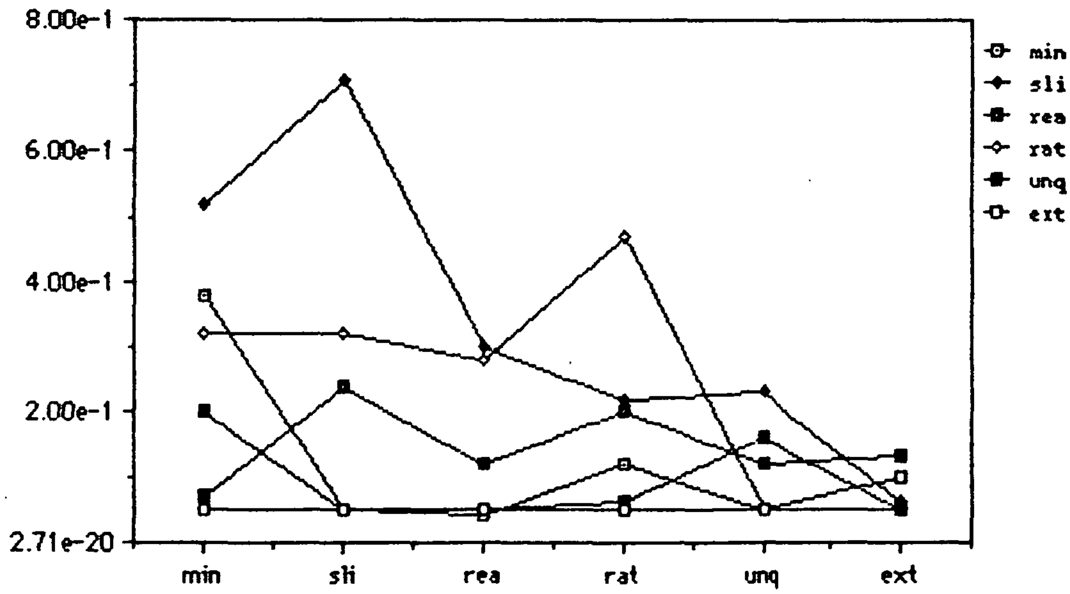

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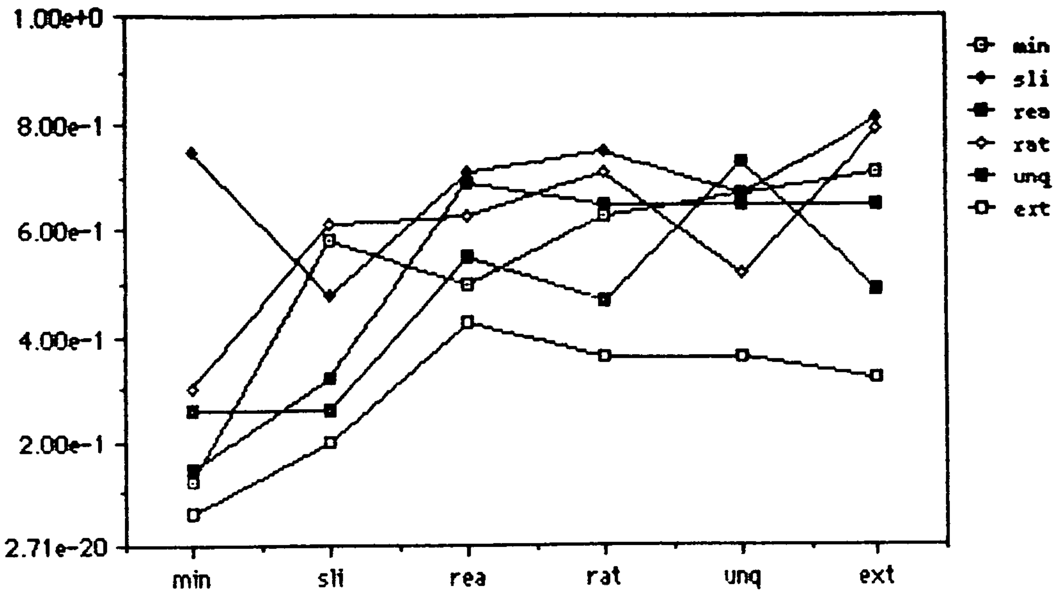

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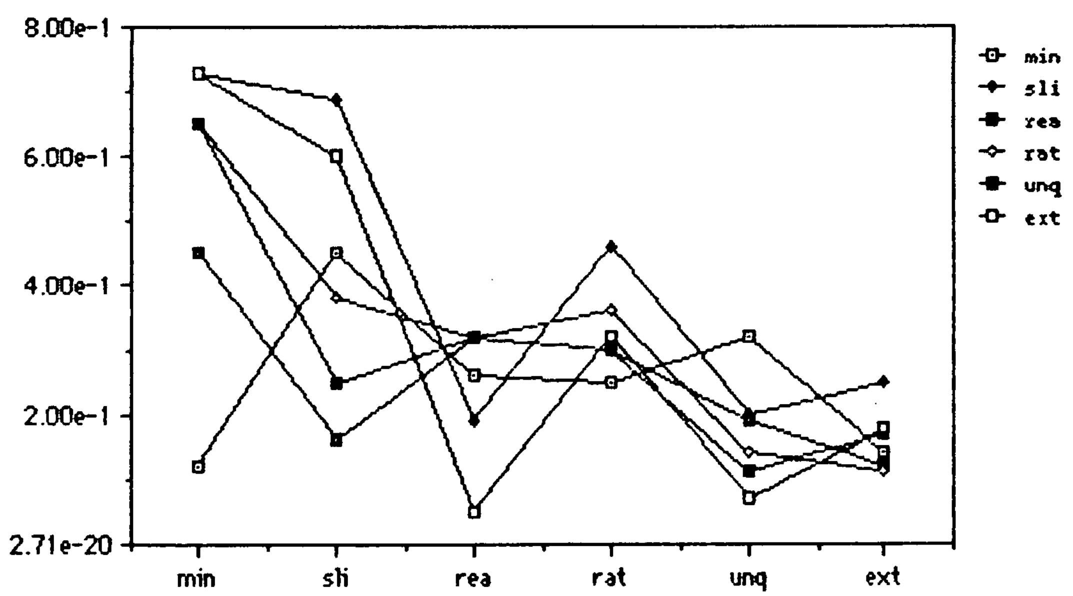

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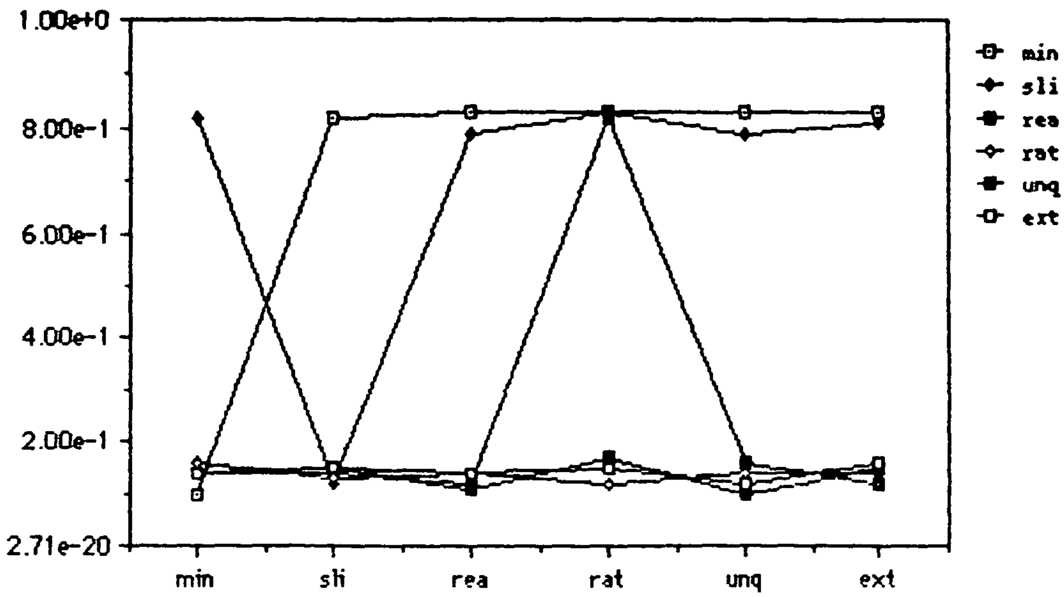

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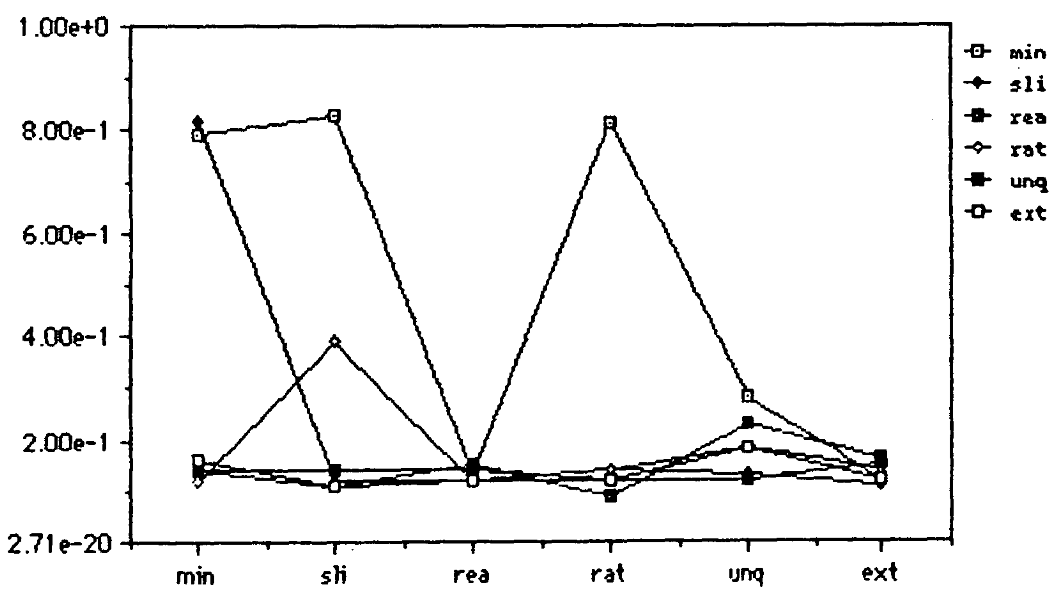

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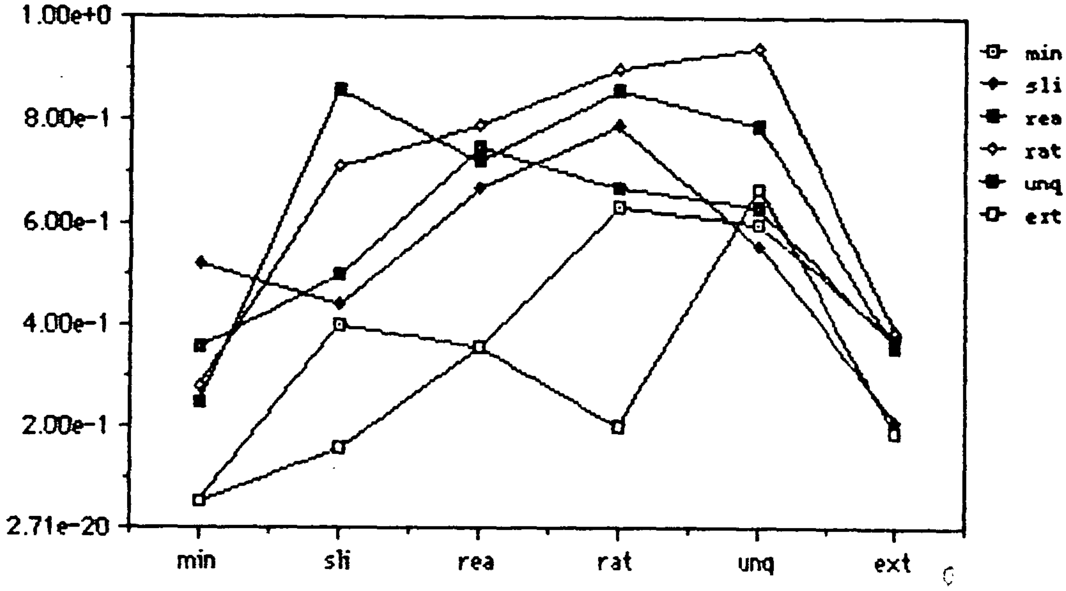

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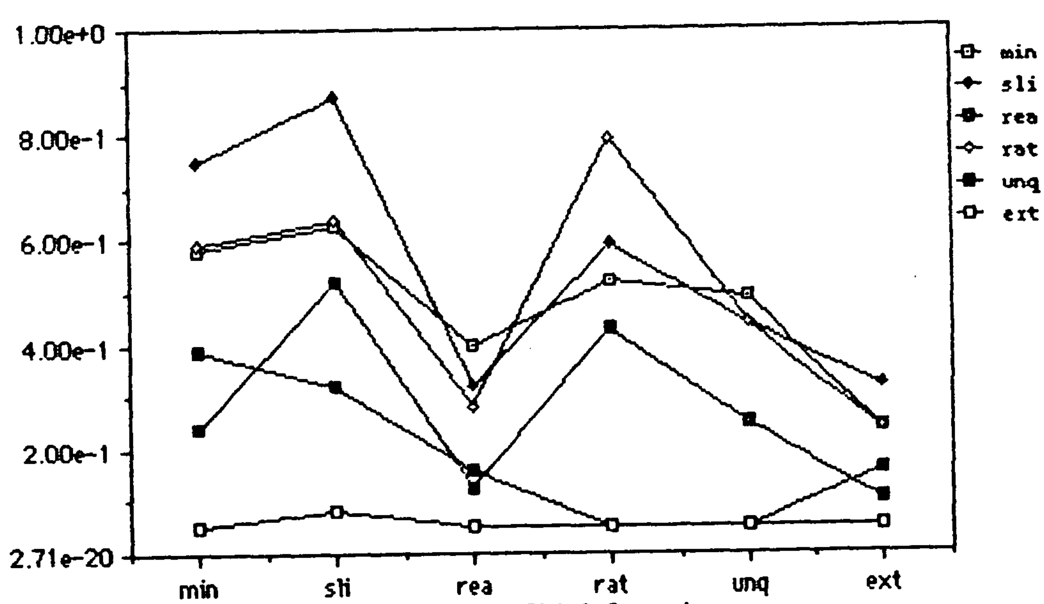

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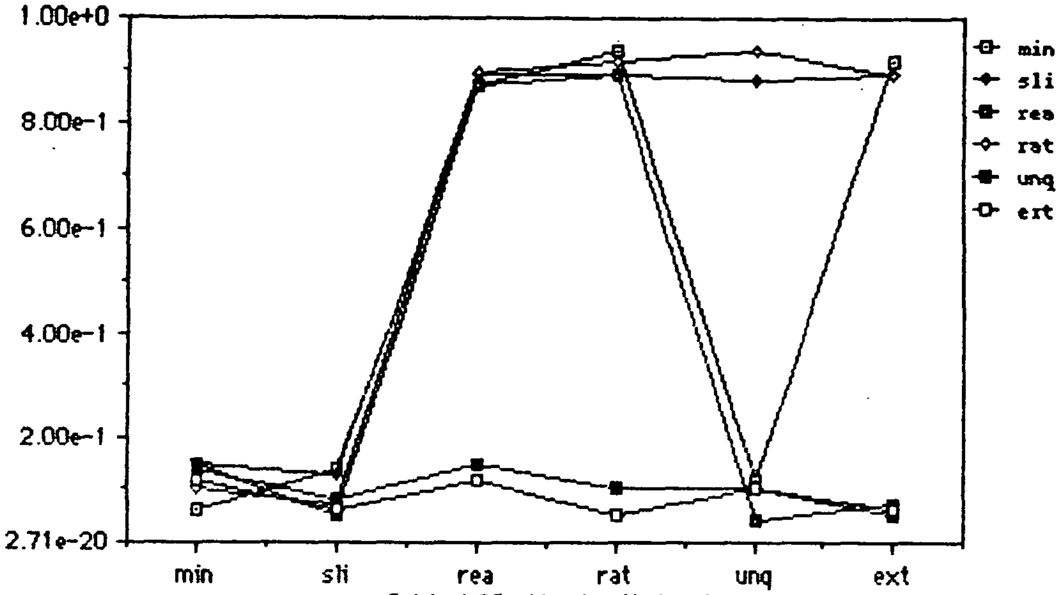

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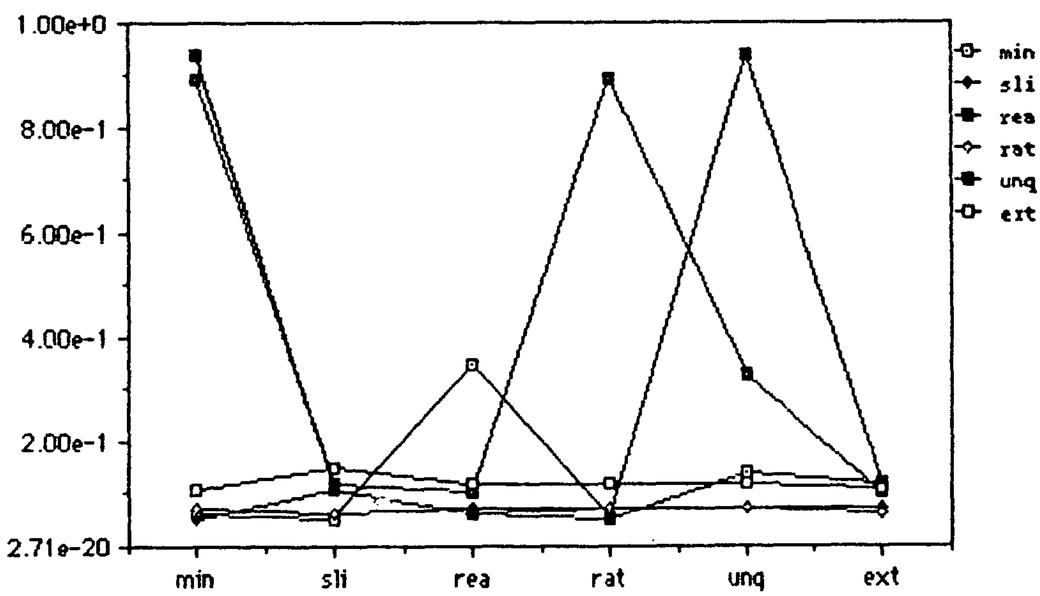

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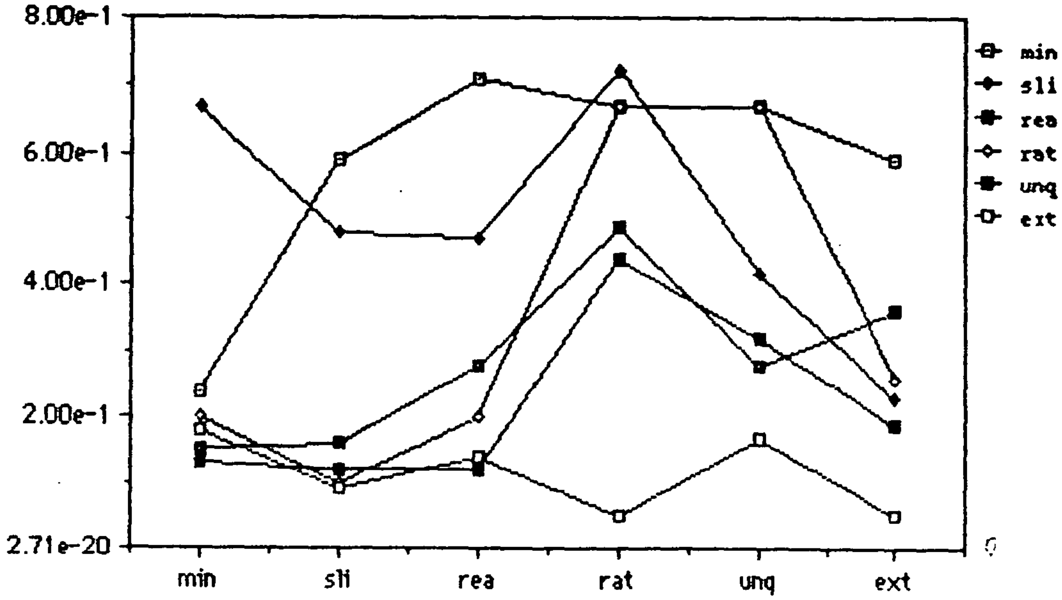

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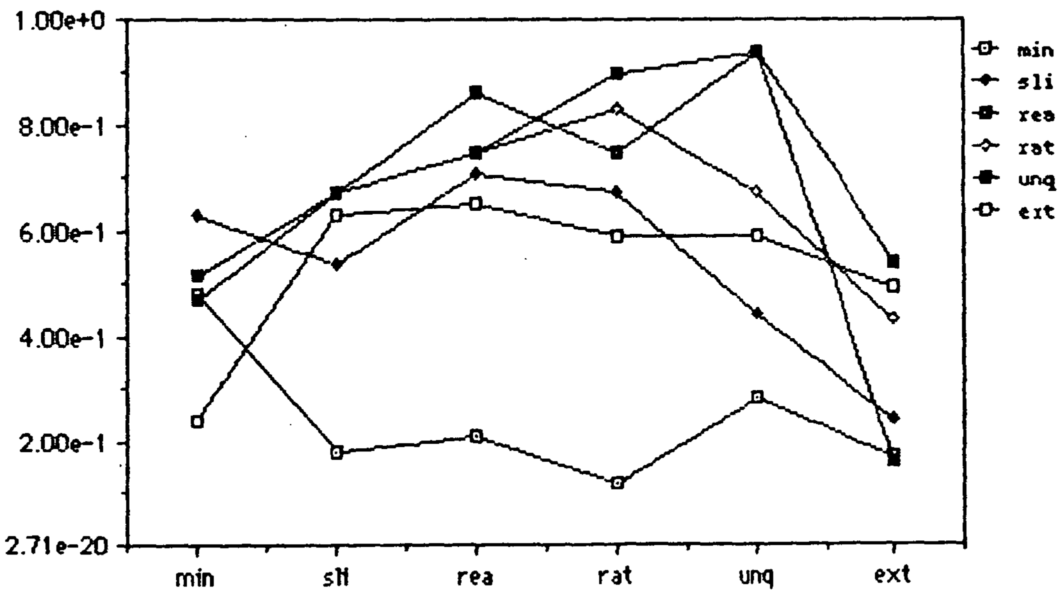

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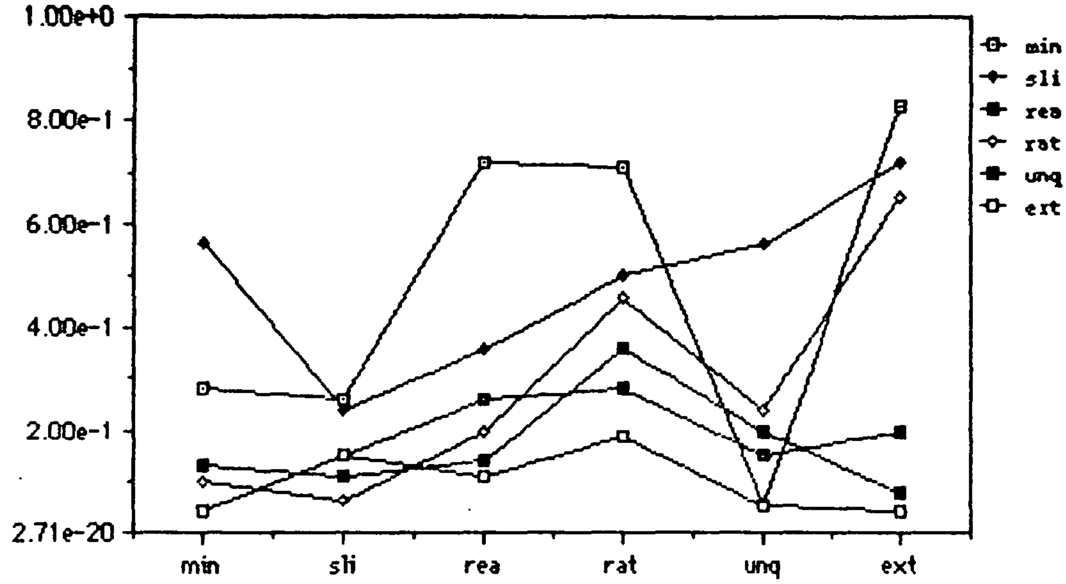

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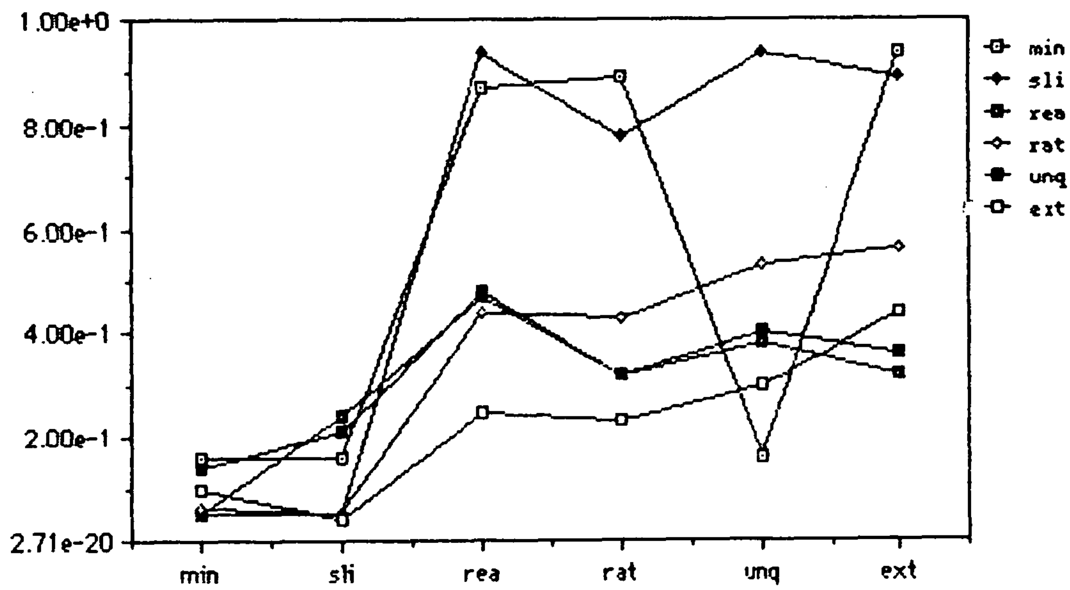

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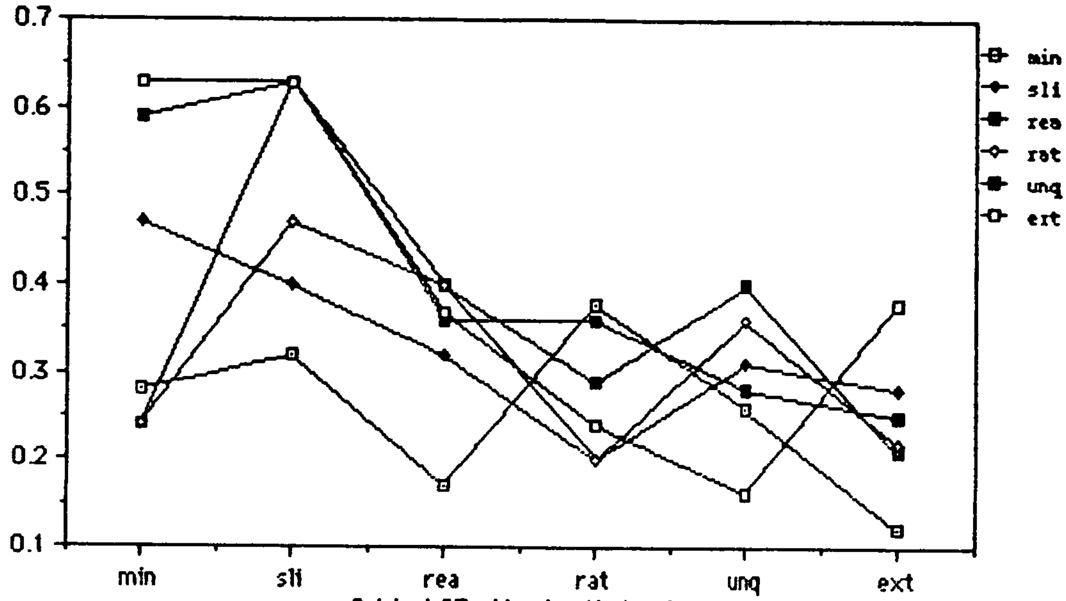

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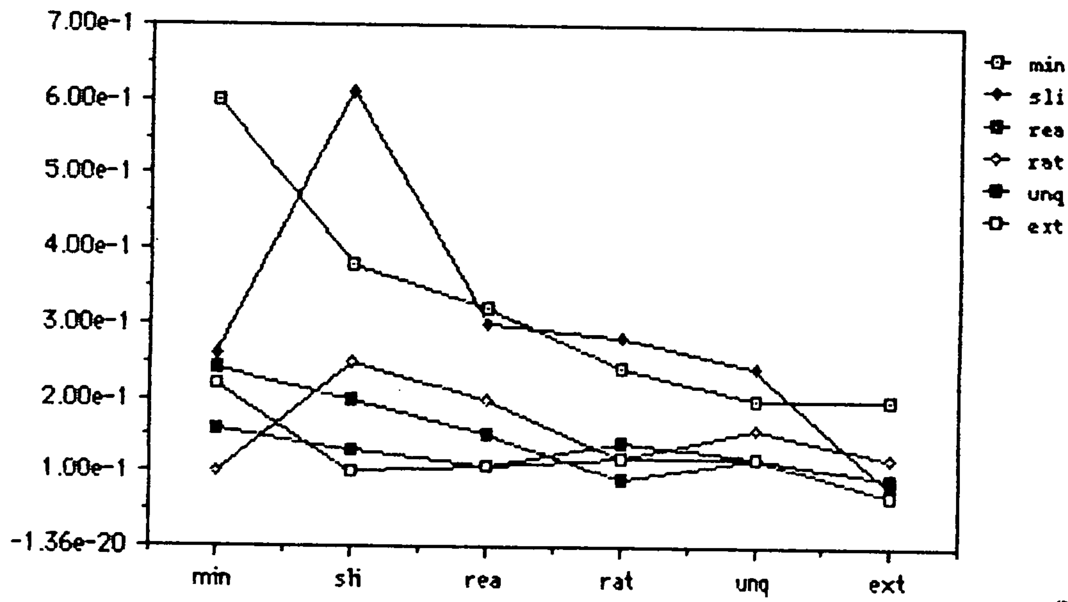

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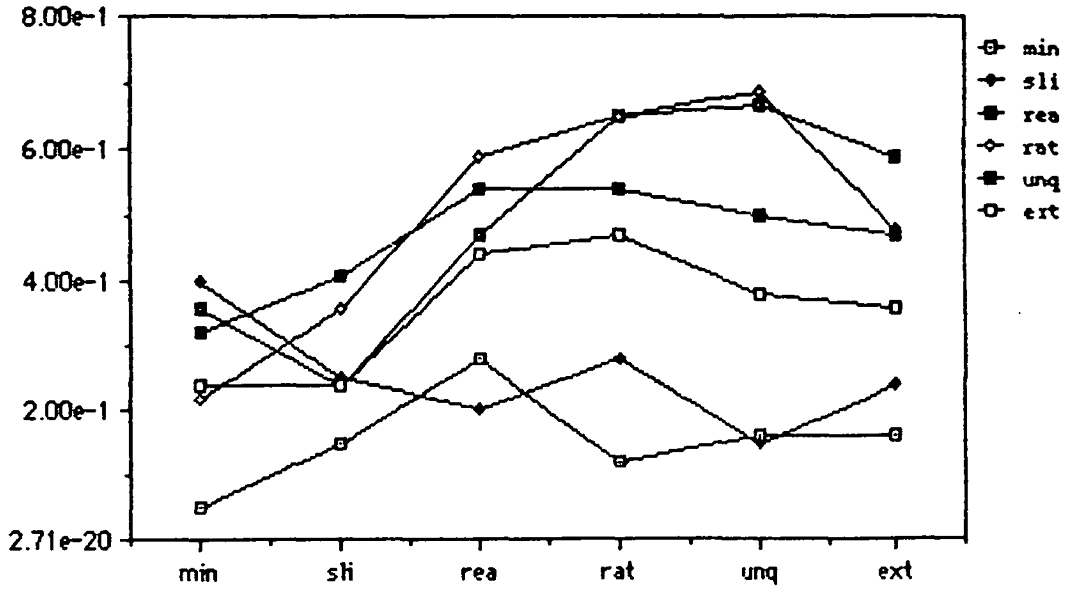

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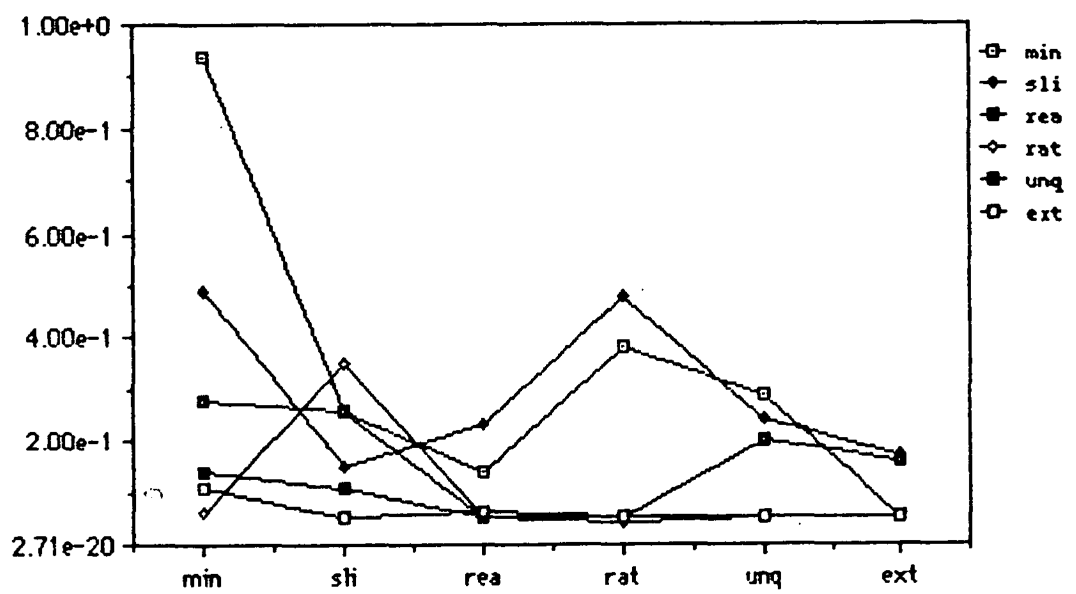

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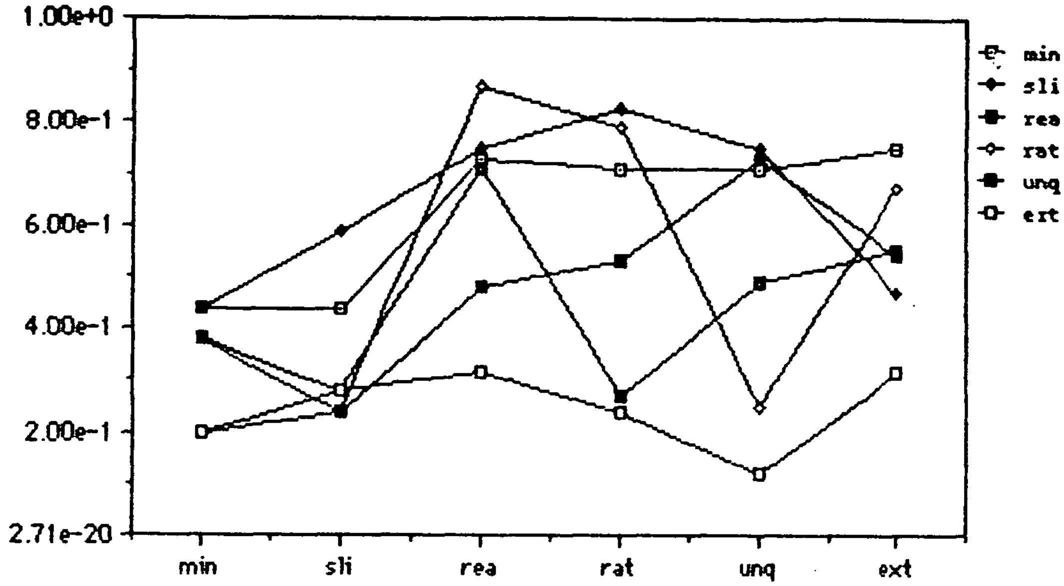

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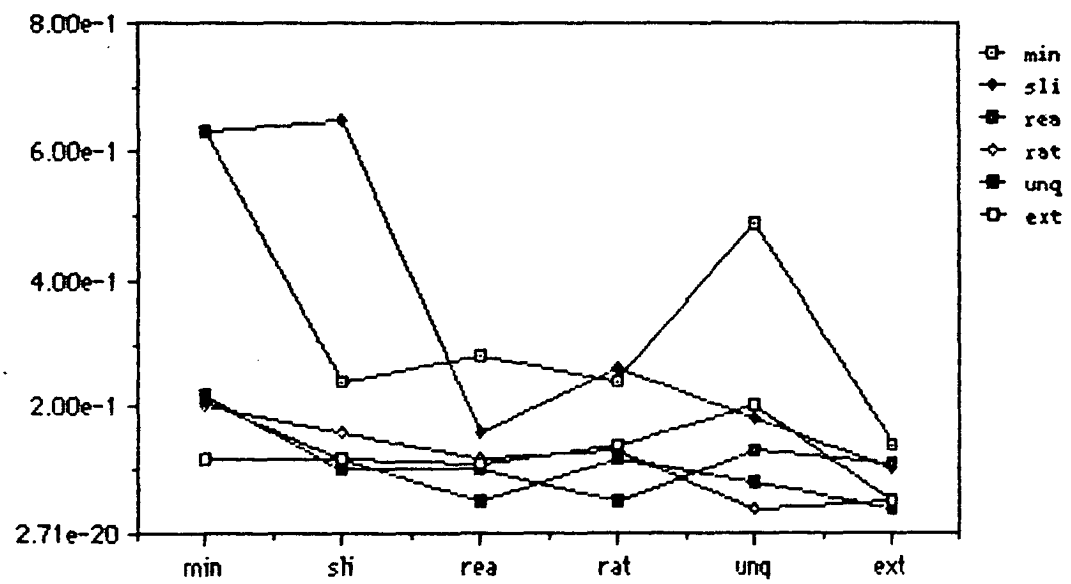

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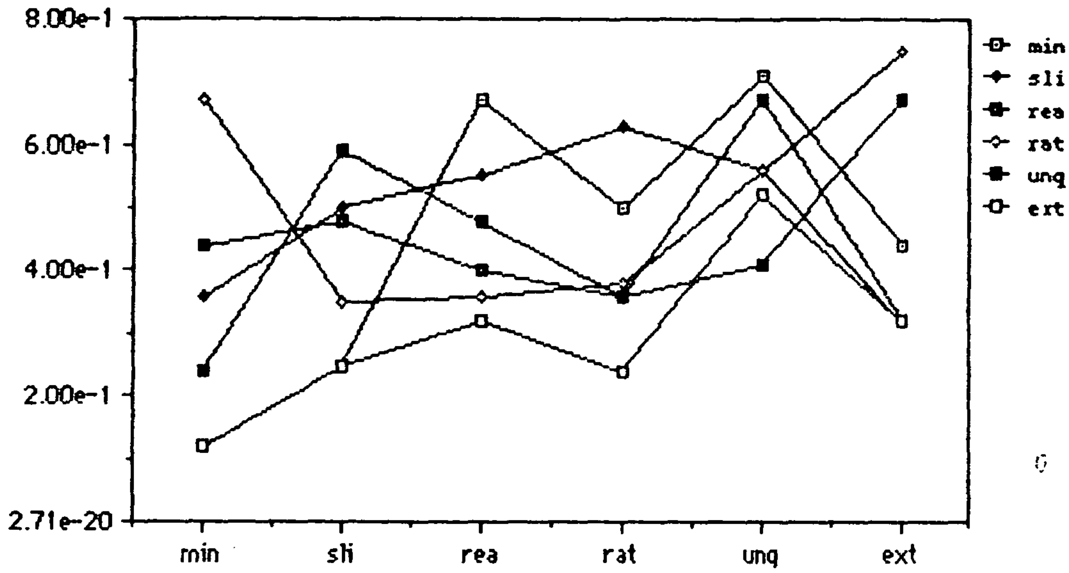

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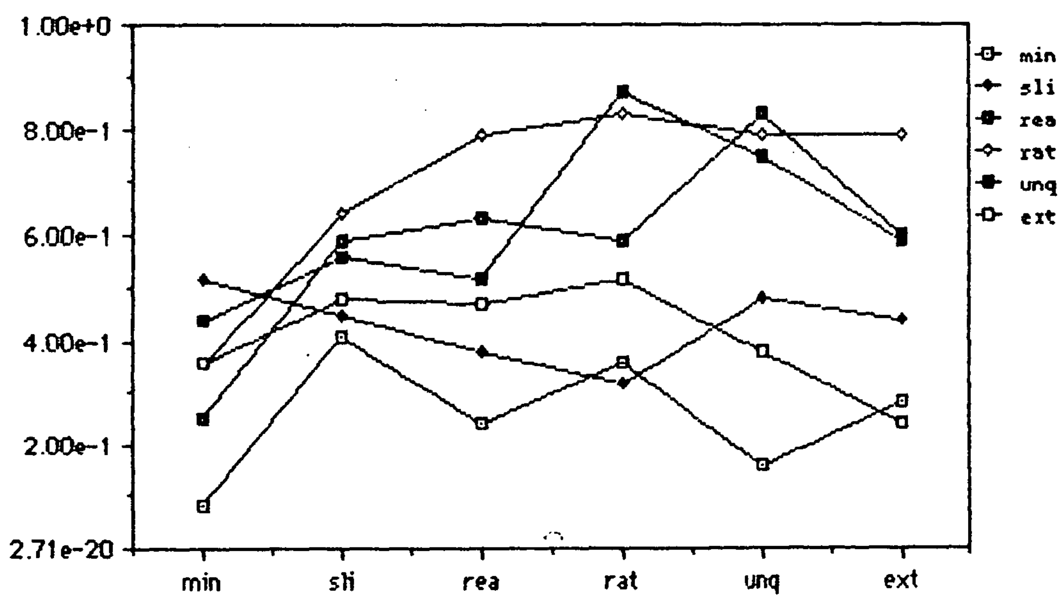

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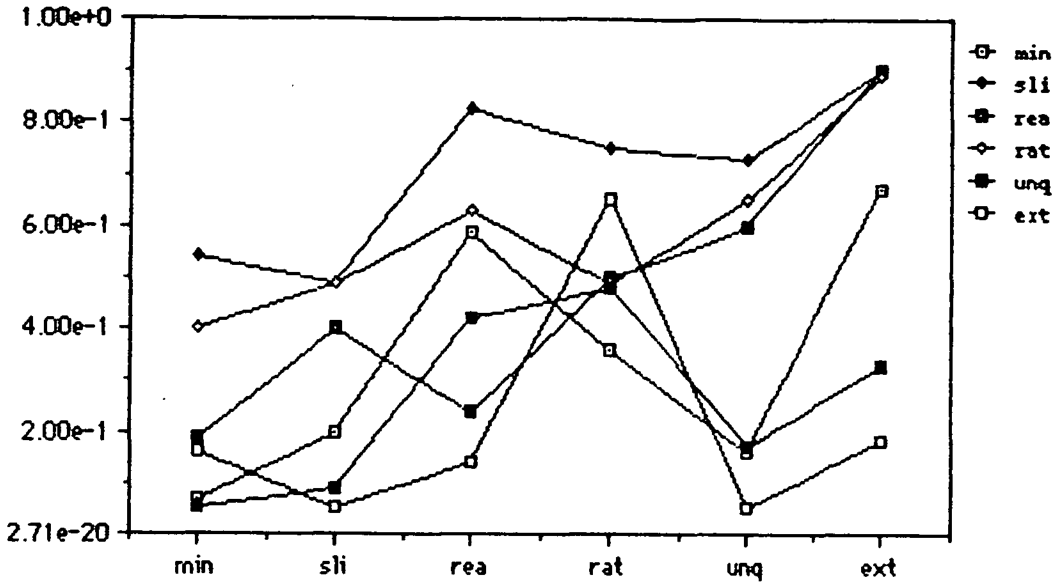

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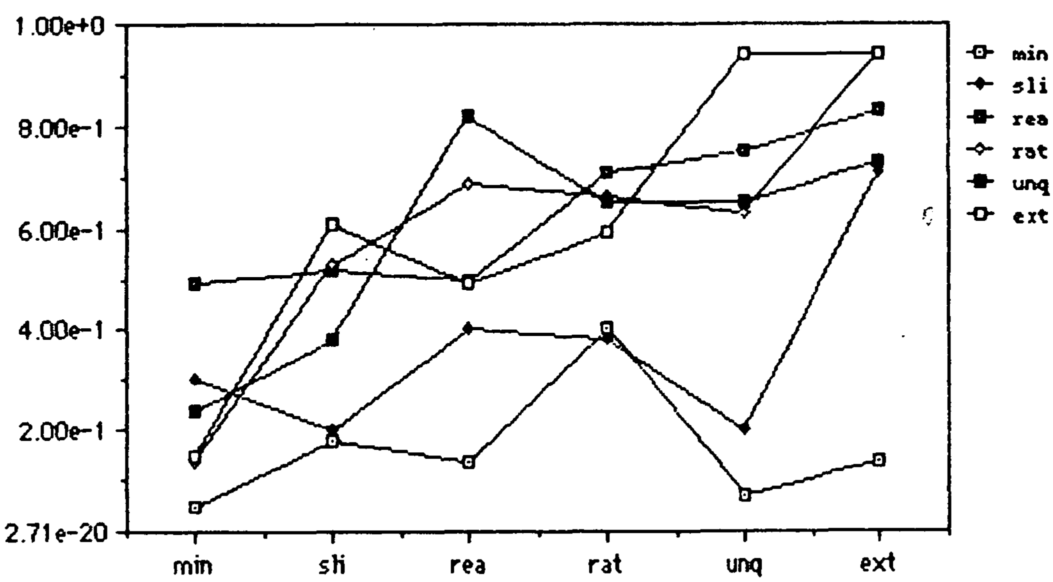

Subject 27, Atomic neg., Concrete

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